Disassembly Design Methods on Material and Component Sustainability Using Multi Criteria Decision Making

A Dissertation Presented by

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要旨

深刻化する資源枯渇や地球温暖化に対処するために，従来の大量生産・大量消費から部品リユースや材料リサイクルといった資源循環を行う持続可能なモノづくりへの転換が求められている．さらに，これらリユース部品やリサイクル材料を使用することで，天然資源からバージン材料を製造する際に排出されるCO_2排出量の削減にも貢献する．しかし，製品に含有する資源が技術的に再生可能にも関わらず資源循環が促進していない原因の 1 つは，再生に必要不可欠な分解はその作業の多様性と複雑さから手分解に頼らざるを得ず，高い人件費から経済的な成立が難しいためである．各部品の材料は製品設計で決定され，廃棄重量やCO_2排出量の環境負荷のみならず，調達・組立・リサイクルコストに影響を与えてしまう．そのため，部品リユースや材料リサイクルにより環境負荷とコストを同時に削減するためには，組立製品の材料選択，分解する部品を決定する分解部品選択と，各プロセスにおける処理個数を決める生産計画の多目的意思決定が必要である．しかしながら，環境負荷とコスト，あるいは環境負荷の目的関数間にはトレードオフの関係が存在するために，複数の環境負荷とコストを同時に削減する解が存在しない場合がある．満足化とは，各目的関数に対して目標値を設定し，それらを満たすような解を求めることであり，目標計画法(Goal Programming; GP)や線形物理的計画法(Linear Physical Programming; LPP)といった手法がある．

本研究では，部品リユースや材料リサイクルを経済的に成立させ促進するために，多目的意思決定を用いた持続可能な材料と部品の分解設計法を提案する．2 章では，多目的意思決定手法の目標計画法と線形物理計画法について説明するとともに，リサイクル率，CO_2排出量や各コストを算出するためのデータベースについて述べる．3 章では，材料選択の意思決定支援モデルについて説明する．製品設計で決定される材料は，廃棄重量や製造時のCO_2排出量のみならず，調達，組立やリサイクルコストにも影響を与える．そのため，環境負荷とコストの多目的評価による材料選択が求められるが，実務では過去の流用設計が中心となっている．したがって，追加の設計時間のために従来検討されなかったが，低環境負荷かつ低コストの材料が存在する可能性がある．本研究では，廃棄重量とCO_2排出量の環境負荷とコストを定量的に算出し，評価する材料決定支援モデルを

開発した．一部の材料変更で，コストを削減しながらも，廃棄重量と CO_2 排出量を同時に達成できるケースがあることを示した．

4 章と 5 章では，どの部品を分解しリサイクルするかを決定するリサイクル率/CO_2 回収率とコストの 2 目的分解部品選択について述べる．組立製品に含有する材料のリサイクルを行うためには，分解が不可欠である．しかしながら，環境負荷とコストを同時に考慮し，どの部品を分解し破棄するかを決定する分解部品選択が必要である．本研究では，目標計画法を用いて，リサイクル率とリサイクルコストおよび CO_2 回収率とリサイクルコストの異なる 2 つの 2 目的分解部品選択法を提案した．ここで，リサイクル率は，使用済み製品のちリサイクルされる部品重量の割合を示し，CO_2 回収率とは，リサイクル材料を使用することで削減できる CO_2 排出量の割合を示している．提案法により，異なる 2 つの分解部品選択法では，リサイクルされる重量の異なるケースの存在がわかった．

6 章では，受注分解生産システムにおける線形物理的計画法を用いた多目的生産計画について説明する．受注分解生産システムには，使用済み製品の回収・分解，部品リユースのための検査や材料リサイクルなどのプロセスが存在し，利益や廃棄重量など複数の目的関数を有する．リユース部品やリサイクル材料の需要を満たすためには，使用状況，回収量や製品種類による使用済み製品の不確実性を考慮し，使用済み製品や部品の個数を決定する生産計画の立案が求められる．本研究では，受注分解生産システムに着目し，線形物理的計画法による多目的生産計画法を提案した．数値実験では，使用済み製品の不確実性のために，回収費用が高い使用済み製品をより多く回収できるケースを発見した．

最後に，7 章では提案した 3 つの設計法の成果をまとめるとともに，今後の課題と展望について述べる．

Abstract

Manufacturing has been required to transform closing the loop of product life cycles for sustainable manufacturing from its linear traditional economic model to deal with serious environmental issues such as material starvation and global warming. Recovery of materials and components embedded in end of life (EOL) products throughout reuse and recycling is one of the effective methods to overcome challenges of the sustainable manufacturing for material circulation. For sustainable manufacturing with material circulation, manufactures need to manage materials throughout design, assembly and disassembly for material recovery with reuse and recycling. Even though materials are decided at a product design phase, the effect of material selection has impact on the entire supply chain including disassembly production. To recover materials in EOL products economically, recyclable materials should be selected at the product design phase. Moreover, disassembly production is required to be designed economically and environmentally friendly. Therefore, this study proposes 3 design approaches, namely material decision support, disassembly parts selection, and disassembly-to-order (DTO) system, for sustainable material management with reuse and recycling with multi-criteria decision making.

Material decision support for disposal weight and CO_2 emissions and cost was developed to provide a chance of whether alternative materials with lower disposal weight, CO_2 emissions and cost, which were not examined in past designs. The proposed decision supports model could find a case where the disposal weight, CO_2 emissions, and total cost were lower 66%, 2% and 1%, respectively than that of default design.

To establish recycling environmentally and economically by selecting parts for disassembly, 2 types of bi-objective disassembly parts selections with recycling/CO_2 saving rate and cost were developed. Both models could find satisfied solutions, which had 60% recycling or CO_2 saving rates and over 60% lower recycling cost than that of all parts disassembled. On the other hand, there were not the same combinations of the selected parts in these bi-objectives. To satisfy the demands for reused components and recycled materials under uncertainties of the EOL product quality, DTO system for reused parts and recycled materials with multiple goals was proposed by using linear physical programming. The design problem with over 200 decision variables was solved with linear mixed-integer programming. Throughout the numerical experiments, a case was

found where the purchaser spent the same cost to buy each different type of EOL product but allocated different purchased amounts to each supplier under the uncertainties of the EOL product.

Chapter 1 states the need of environmentally conscious manufacturing to deal with material starvation and global warming. Chapter 2 introduces solving methods for multi-criteria decision making problems, namely goal programming and linear physical programming, and describes the databases to estimate recyclable weight and CO_2 emissions and costs in the product life cycle; Chapter 3 describes difficulties of material selection to reduce disposal weight and CO_2 emissions and cost simultaneously, and proposes a decision support model for material selection with disposal weight, CO_2 emissions, and cost by liner physical programming; Chapters 4 and 5 explains the relationships among CO_2 saving, recycling rates and cost, and proposes 2 types of bi-objective disassembly parts selection for CO_2 saving/recycling rates and cost; Chapter 6 develops a DTO system to determine the number of EOL products and components for each recovery process such as collecting, inspection and inventory; Chapter 7 concludes the dissertation, and provide directions of future works.

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1. Introduction

Chapter 1 introduces environmental strategies for reuse and recycling all over the world to combat material starvation and global warming, and states the needs of environmentally conscious manufacturing. In Section 1.1, the current situation of reuse and recycling, and environmental regulations and strategies in the world are described by connecting with sustainable development goals (SDGs). Section 1.2 explains a structure of costs, disposal weight and CO_2 emissions in the product life cycle, describes the challenges to establish reuse and recycling economically, and identifies 3 decision making methods between product design and disassembly production phases. In section 1.3, literature review for each decision making method is presented. Section 1.4 gives overviews of the dissertation.

1.1 Background

Manufacturing has been required to transform closing the loop of product lifecycles for environmentally conscious manufacturing from its linear traditional economic model to deal with serious environmental issues such as material starvation and global warming. The environmentally conscious manufacturing is defined as green principles that are concerned with developing methods for whole product life cycle from conceptual design to the end of life (EOL) disposal to meet satisfy environmental standards and requirements (Ilgin and Gupta, 2010).

Environmental awareness and regulations have been pressing manufactures to shift environmental conscious manufacturing (Ilgin and Gupta, 2010). In EU, to boost recycling and waste reduction against the material starvation, circular economy released as a EU's economical strategy package in 2015 (European Commission). The circular economy aims to achieve stable supply of material resources and create new business opportunities including recycling (European Commission).

In a case of Japan, there is a law about recycling basic home electric appliance such as televisions, air conditioners, washing machines and refrigerators as a Japanese recycling strategy. These appliances are regulated to be recycled more than 50% of the EOL products on weight by the law (Japanese Ministry of the Environment).

With respect to regulations to deal with global warming caused by greenhouse gases (GHGs), the Paris agreement has been agreed for implementation by not only the developed nations but also the emerging ones. Each country has the responsibility of setting target values for CO_2 reduction, thus undertaking ambitious efforts to curb climate change (United Nations Framework Conversation on Climate Change). For example, by 2030, Japanese government promised to reduce CO_2 emissions by 26% compared to one in 2013, while Chinese one set the 60-65% reduction target of CO_2 emissions per GDP compared to one in 2005.

Connecting to these environmental regulations and strategies, sustainable development goals (SDGs) consisted of 17 goals were agreed as succession global strategy of Millennium Development Goals by all United Nations Member States in 2015. Sustainable development is "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987). Particularly, among the goals of SDGs, goal 8: "Decent work and economic growth", goal 12 "Sustainable consumption and production" and goal 13 "Climate action" are related to the environmentally conscious manufacturing. This is because recovery of components and materials embedded in EOL products through reuse and recycling can save not only consumption of natural resources but also CO_2 emissions for virgin material production by using reuse components or recycled materials (Igarashi et al, 2016; Kinoshita et al, 2018a; Hasegawa et al, 2019).

Moreover, reuse and recycling have potentials to earn economic benefit. According to the 2016 Recycling Economic Information (REI) report, reuse and recycling activities in the USA created 757,000 jobs and generated \$36.6 billion wages and \$6.7 billion tax revenues in 2007 (U.S. Environmental Protection Agency). However, in the U.S., EOL products are thrown away more than 250 million tons, -two-third of what are become the trash despite of still valuable- each year, according to the U.S. Environmental Protection Agency (Nasr, 2017). In the world, 41.8 billion tons of electrical and electronic equipment become an EOL status every year (Wagner et al., 2019).

Regarding recycling in Japan, Halada et al. (2009) mentioned that even though basic home electric appliances are regulated to be recycled, Japan has considerable surface stocks of metals, called urban mining, which have already been mined and stored in assembly products. These authors estimated that Japanese surface stocks of gold and silver were 2.7 and 3.0 times larger than the world's annual consumption, although Japan has poor natural resources (Halada et al., 2009). Actually, Tokyo 2020 Medal Project succeeded to collect the required amount of metals to make all medals for winner of Tokyo Olympic and Paralympic games from the EOL products such as smartphones and small home appliance products (The Tokyo Organising Committee of the Olympic and Paralympic Games). Therefore, there are economic barriers to disturb the promotion of reuse and recycling. To establish reuse and recycling economically, disassembly design methods between product design and EOL phases in the product life cycle are required since materials and disassembly tasks are already determined in the product design phase.

This study focuses on reuse and recycling of the EOL products, and proposes 3 decision making methods between the product design and disassembly production in the product life cycle to establish them using multi-criterial decision making (MCDM) economically. Next chapter introduces environmental and economic indices for economical decision making for reuse and recycling. Additionally, structure and relationships of these indices are described.

1.2 Structure of costs, disposal weight, and CO_2 emissions in product life cycle

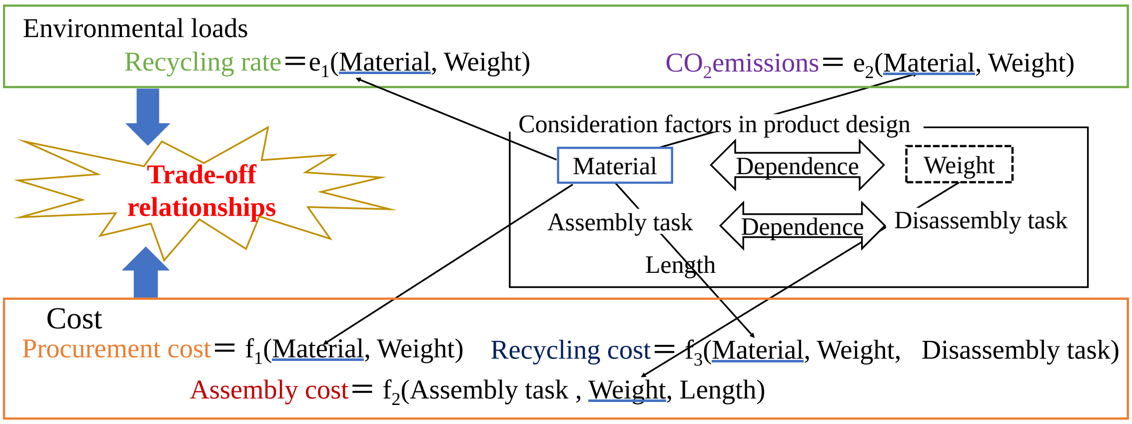

Figure 1.1 Structure of costs, disposal weight and CO_2 emissions among design, assembly and disassembly in product life cycle

In section 1.1, the needs and challenges of the promotion of reuse and recycling economically are explained. Section 1.2 explains the environmental and economic indices for the disassembly design method, and describes structure and relationships of them in the product life cycle. Figure 1.1 shows a structure of costs, disposal weight and CO_2 emissions among design, assembly and disassembly in the product life cycle. This study addresses 2 environmental and 3 economic indices as shown in Fig. 1.1. Each index has 2 or 3 factors to be affected. For example, the recycling rate is affected by the material type and weight for each part. Similar to the recycling rate, the recycling cost is affected by the material type, weight and disassembly tasks. Even though these costs and environmental loads will be helpful at manufacturing and disassembly productions, the factors such as the material, weight and assembly/disassembly tasks to affect those indices are already determined at the product design phase. Additionally, it is found that material types impact on all environmental loads and costs since the weight is dependent of material types as shown in Fig. 1.1 (Kinoshita et al., 2018b).

Therefore, material types decided at a product design phase are one of the important factors to minimize environmental impacts in manufacturing. Moreover, to regain values of components and materials by reuse and recycling, disassembly is an essential and important phase since assembly products are composed of a variety types of components and materials. Therefore, the design method through design and disassembly is required to promote component reuse and material recycling environmentally friendly and

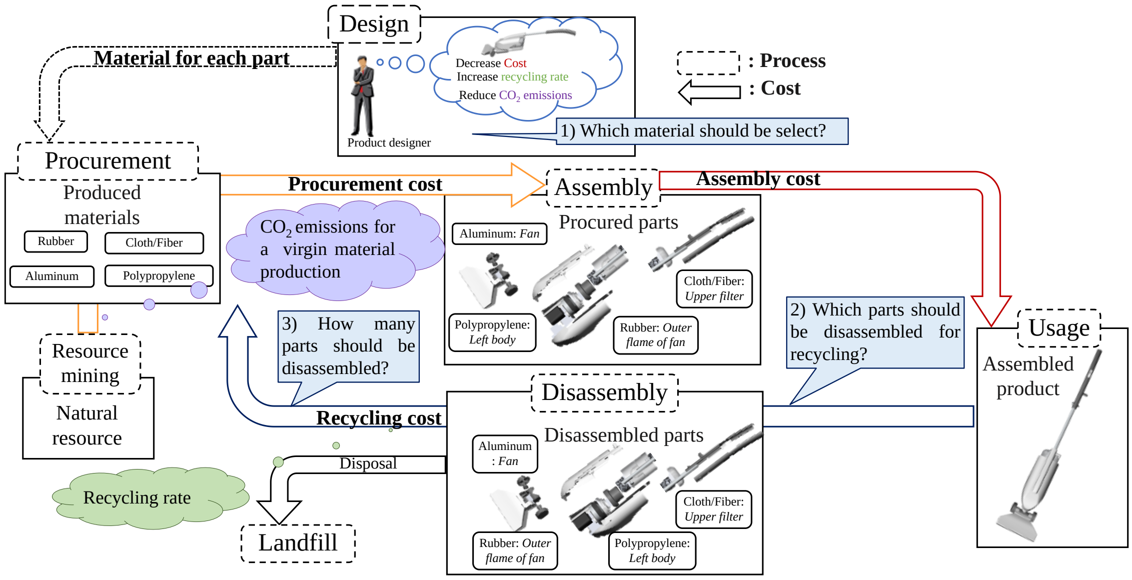

Figure 1.2 Relationships of costs, recycling rate and CO_2 emissions among design, assembly and disassembly in product life cycle: SOLIDWORKS is a registered trademark of Dassault Systèmes SolidWorks Corporation. © 1995-2013, Dassault Systèmes SolidWorks Corporation, a Dassault Systèmes S.A.company, 175 Wyman Street, Waltham, Mass.02451 USA. All Rights Reserved.

economically. However, it is generally known that a trade-off relationship exists between environmental loads and costs (Gupta and Ilgin, 2018; Kinoshita, Yamada and Gupta 2019a).

Figure 1.2 shows relationships of costs, recycling rate and CO_2 emissions in the product life cycle, whose structure is described in Figure 1.1. Dotted squares represent process, while arrows indicate costs in the product life cycle. First, at the product design phase, material type is decided for each part. Material selection in the product design phase will affect procurement cost, assembly cost and recycling costs in manufacturing and disassembly phases as illustrated in Fig 1.1. Similar to such costs, recycling rate at an end-of-life (EOL) phase, and CO_2 emissions for the virgin material production at a procurement phase depend on material types due to different recycling and production processes required for each material type.

After the product design phase, materials are produced from natural resources with CO_2 emissions. Parts made of different materials are assembled at an assembly phase. After a usage phase, the EOL products are collected to regain values of components or materials embedded in the EOL products by reuse or recycling. Disassembly is an essential and important process for component reuse and material recycling since assembly products are consisted of variety types of components and materials. Components are discrete parts and cannot be further disassembled (Lambert and Gupta, 2005). Thus, the terms “parts” and “components” are used as the same meaning in this study. In contrast to assembly, selective or partial disassembly enables to remove specific components in an EOL product with less disassembly cost than that of the complete disassembly. Only selected parts are reused or recycled, while other non-selected parts, which are difficult for neither reuse nor recycling, are crushed for landfill.

By using reused components or recycled materials for assembly products in the next generation, additional CO_2 emissions for the virgin material production can be saved. Reuse is the employment of components and modules obtained from end-of-life products as spare parts or in other items (Lambert and Gupta, 2005). Recycling means the recovery of scrap materials from EOL products (Lambert and Gupta, 2005).

Therefore, as illustrated in Fig. 1.2, the recycling rate and CO_2 emissions can be reduced by components reuse and material recycling in the product life cycle. To establish reuse and recycling economically, here, 3 decision makings through design and disassembly production planning are faced up as shown in Fig. 1.2. First decision making is 1) material selection to reduce cost, disposal weight, and CO_2 emissions in the product life cycle simultaneously since material type determines the potential costs and environmental loads. The second one is disassembly parts selection, which determines the disassembly parts for recycling to balance the recycling/CO_2 saving rates and costs. The CO_2 saving rate can be defined as the rate of the CO_2 volumes in part of assembly products for each disassembled and collected part, which saves the virgin parts/materials to the total CO_2 volumes of the whole product (Igarashi et al., 2014). The last one is disassembly production planning for the disassembly-to-order (DTO) system to satisfy the demands of reused components and recycled materials economically.

Since each decision making has multiple objective functions such as maximizing recycling rate, minimizing CO_2 emissions, and minimizing costs, they are multi-criteria decision-makings. Additionally, it is generally known that a trade-off relationship exists between environmental loads and costs (Gupta and Ilgin, 2018; Kinoshita, Yamada and Gupta, 2019a). Hence, even though decision-makers are usually eager to achieve several goals simultaneously, no optimal solution exists for the trade-off problem (McGovern and Gupta, 2011). In the field of multi criteria decision making, “satisficing as a combination of the words “satisfactory” and “optimizing” is much more prevalent than optimizing in actual practice” (Hillir and Lieberman, 2005). A satisficing solution is a solution where the values of all criteria are sufficient for a decision-maker, even though these values are not the best for each objective. Thus, decision-makers are required to decide on a satisficing solution that reflects their preferences for certain goals by comparing the solutions in terms of their effectiveness and feasibility (Fushimi, Fukukawa and Yamaguchi, 1987). The detailed methods to seek satisficing solutions are stated in chapter 2.

1.3 Literature review

The 3 decision makings through the product design and disassembly production phases are provided to establish component reuse and material recycling economically in section 1.2. In section 1.3, literature reviews for these 3 decision makings are presented. Table 1.1 lists literature review of material selection, disassembly parts selection and disassembly-to-order (DTO) system. “X” in table 1.1 represents that the literature considers an element corresponding to the column. For example, Ashby (2017) addresses the environmental loads in the proposed method.

1.3.1 Literature review of decision support for material selection

Literatures from Ashby (2017) to Chan and Tong (2007) in table 1.1 are related to the decision support model for material selection. The originality of the proposed decision support model for material selection is that it enables to select the recommended materials with mathematical programming by considering procurement/assembly/recycling costs, recycling rate and CO_2 emissions simultaneously in the product life cycle.

Any literatures did not address 3 types of costs, namely procurement, assembly and recycling costs, environmental loads such as recycling rate and CO_2 saving rate simultaneously. However, it can be seen that Romli et al. (2015) and Chan and Tong (2007) are similar to the proposed material selection in this study. To clarify the differences among Romli et al. (2015), Chan and Tong (2007), and proposed material selection, the differences are described in detailed.

The material evaluation method in Romli et al. (2015) was consisted based on quality function deployment. To evaluate the materials by using their proposed methods, it required a lot of sequences procedures. Actually, they used medical forceps with simple design to illustrate the procedure. Hence, it will be difficult to apply the method to product with complex structure such as the assembly products.

On the other hand, there are 2 differences between Chan and Tong (2007) and the decision support for material selection in this study. One difference is the objective functions. Chan and Tong (2007) had only economic objective function such as minimizing costs, while the proposed model in this study has both environmental and economic objective functions, namely minimizing total costs, maximizing recycling rate and minimizing CO_2 emissions.

The other is evaluation methods for material evaluation. The material evaluation methods in Chan and Tong (2007) was based on Gray Relational Analysis (GRA), while the proposed method applies linear physical programming (LPP). According to Gupta and Ilgin (2018), although both of GRA and LPP are solving techniques for multi criteria decision making (MCDM) problems, GRA and LPP are clarified qualitative and quantitative techniques, respectively. Moreover, the evaluation method in Chan and Tong (2007) requires a decision maker (DM) to determine the numerical weights among criteria, even though the weight allocation processes are known to one of the difficult tasks for the DM.

Therefore, originality of the proposed decision support model for material selection is that it can suggest recommended material in terms of environmental and economic aspects with lower time and efforts than the proposed methods in Romli et al. (2015) and Chan and Tong (2007). The lower time and efforts for material evaluation is brought by using LPP to solve the MCDM problem.

Table 1.1 A literature review of decision support models for material selection (MS), disassembly parts selection (DPS), and disassembly-to-order system (DTO)

No.	Literatures		Evaluation index						Decision support			Material type	Life cycle option				Life Cycle Assessment (LCA)	Disassembly Precedence Relationships	Design example	
			Cost			Environment														
			Procurement	Assembly	Disassembly/Recycling	Environmental loads	Recycling rate	CO_2 emissions	MCDM	Quantitative Technique	Remove weight allocation		Collecting	Reuse	Recycling	Disposal			Product type	Number of Applied Parts
1	Ashby (2017)	MS				X						X								
2	Holloway (1998)	MS				X						X								
3	Farag and El-Magd (1992)	MS	X						X			X							Sailing-boat mast	1
4	Johnson and Kirchain (2009)	MS	X	X								X							Automotive instrument panel beam	4
5	Rahman et al (2012)	MS	X	X		X			X			X							Pitched roof	-
6	Serafini Russo and Rizzi (2015)	MS				X		X	X		X	X					X		I-beam	1
7	Cheung et al. (2015)	MS			X					X		X			X	X		X	Multi-functional display unit in cockpit	3
8	Aguiar et al. (2017)	MS			X	X	X					X	X		X	X			CD player	38
9	Romli et al (2015)	MS	X		X	X	X	X	X			X		X	X	X	X		Medical forceps	1
10	Chan and Tong (2007)	MS	X	X	X				X			X		X	X	X			Vacuum cleaner	1
This study		MS	X	X	X	X	X	X	X	X	X	X			X	X	X		Vacuum cleaner	5
		DPS			X	X	X	X	X	X	X	X			X	X	X	X	Vacuum cleaner	23
		DTO			X	X	X		X	X	X	X	X	X	X	X			Desktop computer	14

Continued

No.	Literatures		Evaluation index						Decision support			Material type	Life cycle option				Life Cycle Assessment (LCA)	Disassembly Precedence Relationships	Design example	
			Cost			Environment														
			Procurement	Assembly	Disassembly/Recycling	Environmental loads	Recycling rate	CO_2 emissions	MCDM	Quantitative Technique	Remove weight allocation		Collecting	Reuse	Recycling	Disposal			Product type	Number of Applied Parts
11	Dong, Gibson and Arndt (2007)				X										X			X	C-clamp	4
12	Teunter (2006)				X										X	X		X	Fictional product	5
13	Kang et al. (2016)				X					X					X			X	2 types of fictional products	11 parts (total)
14	Kongar and Gupta (2006)				X							X		X	X			X	Fictional product	10
15	Rickli and Camelio (2014)	DPS			X				X					X	X	X		X	Solenoid valve	7
16	Seo, Park and Jang (2001)				X	X						X			X	X	X	X	Door in refrigerator	14
17	Smith, Hsu and Smith (2016)				X	X						X			X	X	X	X	Drive assembly	10
18	Rickli and Camelio (2013)				X	X			X			X			X	X	X	X	Coffee maker	66
19	Okumura et al. (2016)				X	X		X				X		X	X	X		X	Inkjet printer	31
20	Massoud and Gupta (2010)				X				X	X	X		X	X	X	X			3 types of fictional products	10 parts (total)
21	Ondemir and Gupta (2014a)				X	X	X		X	X	X	X		X	X	X		X	Dryer	12
22	Ondemir and Gupta (2014b)	DTO			X	X			X	X	X	X		X	X	X		X	Air-conditioner	10
23	Joshi and Gupta (2017)				X	X			X	X	X	X		X	X	X		X	4 types of air-conditioner	8
24	Joshi and Gupta (2019)				X	X			X	X	X	X		X	X	X		X	3 types of laptop	10
This study		MS	X	X	X	X	X	X	X	X	X	X			X	X	X		Vacuum cleaner	5
		DPS			X	X	X	X	X	X	X	X			X	X	X	X	Vacuum cleaner	23
		DTO			X	X	X		X	X	X	X	X	X	X	X			Desktop computer	14

1.3.2 Literature review of disassembly parts selection

With regards to related literatures about disassembly parts selection, there are 9 literatures listed in table 1.1. Similar to the decision support model for material selection, originality of the bi-objective disassembly parts selection is that the model can evaluate disassembled parts from the end-of-life (EOL) products in terms of environmental and economic aspects simultaneously using mathematical modeling. Dong, Gibson and Arndt (2007), Teunter (2006), Kang et al. (2012), Kongar and Gupta (2006) and Rickli and Camelio (2014) did not have environmental objective functions such as maximizing recycling rate to determine the disassembled parts, even though disassembly plays an important role for recycling.

In contrast to those literatures, Seo, Park and Jang (2001), Smith, Hsu and Smith (2016), Rickli and Camelio (2013) and Okumura et al. (2016) had both environmental and economic objective functions. However, all of them did not applied mathematical modeling methods such as goal vector method by goal programming (GP). They used simulation, GA and cost-benefit analysis instead of the mathematical modeling. Thus, their method would take longer time and much efforts than that of proposed model to determine the disassembly parts. By using mathematical modeling with GP, the proposed model can seek multiple solutions by only changing the target ranges of the objective functions. Therefore, the proposed bi-objective disassembly parts selection can support a DM to determine disassembly parts by comparing multiple obtained solutions with less efforts and shorter time than those models.

1.3.3 Literature review of disassembly-to-order (DTO) system

Regarding to the DTO, there are 5 literatures listed from Massoud and Gupta (2010) to Joshi and Gupta (2019) in table 1.1. The originalities of the proposed DTO is that the DTO involves the decision making for collecting the number of the EOL products for each type, and have an environmental objective function such as maximizing recycling rate.

Massoud and Gupta (2010) did not have any environmental objective functions, and then their model had only economic objective functions. Additionally, the model in Massoud and Gupta (2010) could not evaluate each material type of the disassembled components. Then, the model could not determine the required number of the components to satisfy the demand of a certain type of material.

In Ondemir and Gupta (2014a, 2014b), Joshi and Gupta (2017, 2019), although each of them had environmental objective function, literatures except of Ondemir and Gupta (2014a) did not evaluate the recycling rate of the determined disassembly production planning in their models directory. This is because the environmental objective functions in Ondemir and Gupta (2014b) and Joshi and Gupta (2017, 2019) evaluate the number of disposed components or disposal costs, even though the one of the importance index related to recycling is the actual recycled weight against the total collected weight indeed. Therefore, the proposed DTO can determine the required number of the EOL products under minimizing costs and maximizing recycling rate.

1.4 Overview of proposed models and d organization

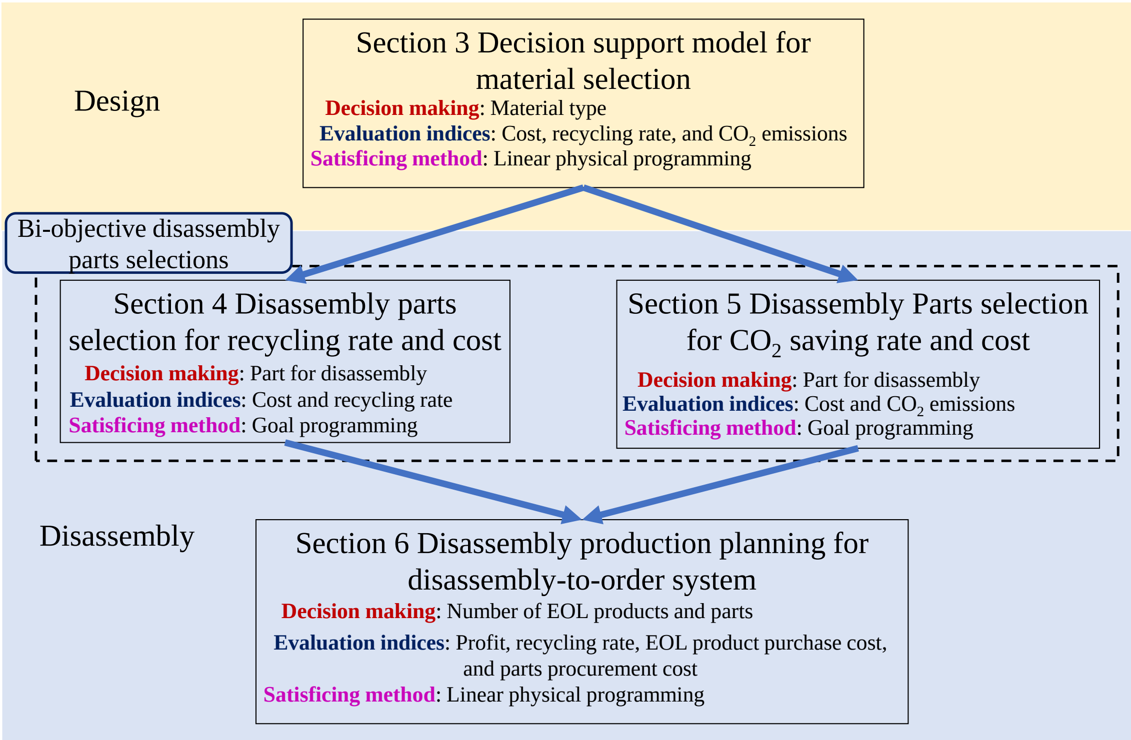

Figure 1.3 Overview of proposed models and thesis organization

This study focuses on the design and disassembly phases in the product life cycle to promote component reuse and material recycling environmentally friendly and economically, and proposes 3 types of design methods with multi criteria decision making to reduce disposal weight, CO_2 emissions and cost simultaneously. The 1st design method is decision support model for material selection. The 2nd one is 2 types of bi-objective disassembly parts selections. The last one is disassembly production planning in the DTO system with multiple goals. The overview of the proposed models and sections are represented in Fig. 1.3. The proposed 3 decision making methods are deterministic models. Hence, the same solutions will be obtained by using the same input data for each proposed method.

The rest of this thesis is organized as follows: Chapter 2 introduces multi criteria decision making techniques, namely goal programming and linear physical programming, and databases to estimate environmental and economical indices including as recycling rate, CO_2 emissions, and procurement/assembly/recycling costs. Chapter 3 proposes the decision support model for material selection for cost, disposal weight and CO_2 emissions using LPP. Chapter 4 presents one bi-objective disassembly parts selection for recycling rate and cost, discusses the results of different assembly products, and examines the effects of target ranges of goal programming on the combinations of selected parts. Chapter 5 suggests another bi-objective disassembly parts selection for CO_2 saving rate and cost, and compares the results of 2 different types of bi-objective disassembly parts selections. Chapter 6 proposes a disassembly production planning method in disassembly-to-order system to satisfy demands of reused components and recycled materials. Finally, Chapter 7 summarizes the 3 proposed design methods and gives directions for future studies.

2. Multi criteria decision making techniques and databases for environmental and economic indices

Chapter 1 states the needs of reduction of the disposal weight and CO_2 emissions through component reuse and material recycling, and identifies the structure of costs, recycling rate and CO_2 emissions in the product life cycle. To design disassembly methods for promotion of the component reuse and material recycling economically, multi criteria decision making (MCDM) techniques, namely goal vector method by goal programming (GP) and linear physical programming (LPP), and information for each part in assembly product are required. Chapter 2 introduces MCDM techniques, and explains the required information for each part. First, section 2.1 describes advantages and features of GP and LPP. Section 2.2 defines a bill of materials including the recycling rate and CO_2 emissions.

2.1 Multi criteria decision making techniques

The multi criteria decision making (MCDM) techniques have recognized as the considerable and appropriate tools to evaluate environmental and economic benefits simultaneously for environmental conscious manufacturing (Ilgin, Gupta and Battaïa, 2015; Gupta and Ilgin, 2018), since these techniques are suitable of modeling conflicting objectives such as maximizing of the profit and minimizing the environmental impacts (Gupta and Ilgin, 2018). To seek satisficing solutions with quantitative techniques, a decision maker (DM) is generally required to determine the priority or mathematical weight among multiple criteria directly or indirectly (Ilgin, Gupta and Battaïa, 2015; Messac, Gupta and Akbulut 1996).

However, determination of ether priority or mathematical weight is difficult for the DM due to 2 reasons (Lee, 1972, Ignizio, 1976, Messac, Gupta and Akbulut 1996; Fushimi, Fukukawa and Yamaguchi, 1987). One reason is that each criterion usually have different unit or scales. Additionally, there is no guarantee that the numerical weight can reflect to correct desirability of the objective functions for the DM. For example, if the DM wants to achieve 60% recycling rate, how to set the numerical weight w? Which values w=0.1, w=10, w=100 are suitable? Or another value is more suitable? It is difficult to predict to the correct numerical weight before seeking the solution obtained with the weight. Usually, the DM needs trial and error to adjust the numerical weight based on the obtained solutions.

The other reason is that the DM is often eager to achieve or improve all criteria simultaneously (Lee, 1972; Fushimi, Fukukawa and Yamaguchi, 1987). That leads to difficulty to prioritize among criterion. Thus, the DM has trouble to express his/her preferences for criteria as correct mathematical weight (Lee, 1972, Ignizio, 1976, Messac, Gupta and Akbulut 1996; Fushimi, Fukukawa and Yamaguchi, 1987).

To overcome these issues, goal vector method by goal programming (GP) and linear physical programming (LPP) were developed by Fushimi, Fukukawa and Yamaguchi (1987) and Messac, Gupta and Akbulut (1996), respectively. One of the common feature of them is that the DM is required only to set desirability ranges for each criterion instead of using weight allocation process. It is generally available for the DM to grasp the desired direction (Messac, Gupta and Akbulut, 1996), for example, minimizing or maximizing, etc., and easer to determine the desirability ranges for each criterion than setting target value directly and prioritizing. Therefore, this study applies GP and LPP to 3 design methods. The summary of GP and LPP are explained in subsection 2.1.1 Subsections 2.1.2 and 2.1.3 describes the detailed procedures of GP and LPP, respectively.

2.1.1 Overview of GP and LPP

As described in section 2.1, GP and LPP were developed to overcome difficulties of the weight allocation processes in MCDM. Both of them require the DM to set desirability ranges for each criterion instead of the conducting mathematical weight allocation process. On the other hand, GP and LPP also have different features. The features of GP and LPP are summarized in table 2.1. To clarify the advantages of GP and LPP, weighted sum method and epsilon constraint method are also shown in table 2.1.

Comparison of weighted sum method, epsilon constraint method, GP and LPP

Here, it is assumed that there are 3 objective functions; $f_1(x)$, $f_2(x)$ and $f_3(x)$. The $f_1(x)$ and $f_3(x)$ are minimized, while $f_2(x)$ is maximized. Weighted sum method (Marler and Arora, 2009) requires the DM to determine the numerical weights w_1 w_2 w_3 among criterion directly as shown in an aggregate objective function. One of the advantages of weighted sum method is easy to be applied. However, as mentioned in section 2.1, the determination of the correct numerical weight directly is one of the different tasks for the DM. The epsilon constraint method is one of the solving methods of MCDM problems. Instead of weight allocation processes, the epsilon constraint method needs to determine one primary objective function, while other objective functions are transposed to constraints with epsilon (Eskandarpour et al. 2015). By changing the values of the epsilon, epsilon constraint method can obtain Pareto-optimal solutions. One of the advantages of epsilon constraint method is that it can prioritize only one criterion. In constraint, one of the disadvantage of it is that the required number of numerical experiments for sensitivity analysis will be increased rapidly if the number of objective functions is increased.

Regarding to GP and LPP, both of them require the decision maker (DM) to set desirability ranges for each criterion instead of determining numerical weight direly or target for each criterion like weighted sum method and epsilon constraint method. However, GP and LPP should be applied to the different types of MCDM problems, respectively.

Differences between GP and LPP

GP requires the DM to grasp the feasible maximum and minimum values of each criterion in order to obtain a feasible solution since GP can set only one desirability range for each criterion. Therefore, GP should be applied to MCDM problems, in which the maximum and minimum values of each criterion can be grasped. As one of the advantages of GP, it can conduct sensitivity analysis by changing only target values to seek a satisficing solution.

On the other hand, LPP should be adopted to MCDM problems, in which the maximum and minimum values of each criterion are difficult to be grasped. In contrast to GP, LPP can set 6 different types of desirability ranges at the same time. Then, the wider desirability ranges than that of GP will be helpful to obtain a feasible solution, if the DM does not know the feasible maximum and minimum values of each criterion. Regarding to sensitivity analysis with changing the desirability ranges in LPP, it needs to recalculate the LPP weight based on its algorithm. Therefore, LPP will take longer time and much efforts than GP to conduct sensitivity analysis.

Adaptation of GP and LPP to MCDM problems

In bi-objective disassembly parts selections in chapters 4 and 5, the maximum and minimum total recycling, CO_2 saving rates and costs can be grasped from a bill-of-materials (BOM) since all of them can be increased or decreased if the parts are selected for disassembly only. Thus, GP is suitable for the bi-objective disassembly parts selection to seek a satisficing solution.

With regarding to decision support model for material selection in chapter 3, it determines material type with different disposal weight, CO_2 emissions and costs for each part. Then, it is difficult to guess the maximum and minimum of values of each criterion. Additionally, in multi-criteria disassembly production planning in disassembly-to-order (DTO) system, the decision making is to determine the number of EOL products or components for each recovery process in the DTO. Moreover, each recovery process is not dependent. Hence, it is also difficult to grasp the maximum and minimum of values of each criterion. Therefore, LPP should be adopted to the decision support model for material selection in chapter 3 and the multi-criteria disassembly production planning in the DTO system in chapter 6.

By setting desirability ranges by the DM, 2 cases will occurred. One case is that the DM sets non-feasible range as the desirability range for a certain criterion. In this case both of GP and LPP cannot find any solutions. Another case is that the DM sets feasible range as the desirability range for all criteria. In this case, GP and LPP can seek one solution to minimize value of an aggregate objective function from feasible solutions.

In a case that an aspiration level of a certain criteria would be difficult to become desirable or ideal, 2 causes can be considered. One cause is that there could be tradeoff relationships among criteria. Whether there are trade of relationships or not can be observed from the results of single objective models for each criterion. If the results of single models show that all criteria cannot be reach in ideal or desirability ranges, simultaneously, there would be tradeoff relationships among criteria.

The detailed features and procedures of GP and LPP are described in subsections 2.1.2 and 2.1.3.

Table 2.1 Summary of weighted sum method, epsilon constraint method, GP and LPP

MCDM techniques	Weighted sum method (Marler and Arora, 2009)	Epsilon constraint method (Eskandarpour et al. 2015)	Goal vector method by goal programming (GP) (Fushimi, Fukukawa and Yamaguchi, 1987)	Linear physical programming (LPP) (Messac, Gupta and Akbult, 1996)
Aggregate objective function	Linear sum of multi criteria using mathematical weights $J = w_1 f_1(x) - w_2 f_2(x) + w_3 f_3(x) \rightarrow Min$	Selected one primal objective function among multi criteria $J = f_1(x) \rightarrow Min$	Minimizing average and maximum deviation variables with parameter β $J = \beta \frac{d_1^+ + d_2^- + d_3^+}{3} + (1-\beta)d \rightarrow Min$	Sum of products of calculated LPP weight and deviation variables $J = \sum_{i=1}^{3} \sum_{s=2}^{5} (\widetilde{w}_{is}^+ d_{is}^+ + \widetilde{w}_{is}^- d_{is}^-) \rightarrow Min$
Weighting/Normalizing among criteria	Determine mathematical weight directly by a DM	-	Use difference between sufficient and tolerable levels for each criterion	Calculate mathematical weight based on LPP weight algorithm operated with One vs. Others rule
Unique procedures	Conduct weight allocation by a DM based on his/her experiences	Introduce epsilon ε_2 and ε_3 for non-primary criteria to get Pareto optimal solutions	Set sufficient and tolerable levels for each criterion	Allocate one soft or hard class from 4 different types of classes to set desirability ranges
Advantages	Easy to formulate and get solutions	・Enable to prioritize one criterion by selecting primal objective function ・Easy to conduct sensitivity analysis	・Need not weight allocation among criteria ・Evaluate different criteria with different units or scales normally ・Easy to conduct sensitivity analysis	・Need not weight allocation among criteria ・Enable to set 6 desirability ranges for each criterion at once ・Calculate correct LPP weight automatically to reflect desirability of a DM

Continued				
MCDM techniques	Weighted sum method (Marler and Arora, 2009)	Epsilon constraint method (Eskandarpour et al. 2015)	Goal vector method by goal programming (GP) (Fushimi, Fukukawa and Yamaguchi, 1987)	Linear physical programming (LPP) (Messac, Gupta and Akbult, 1996)
Disadvantages	Struggle to determine the correct mathematical weight to reflect desirability of DM	Need sensitivity analysis by changing epsilon to get a satisficing solution	Need the sensitivity analysis by changing combinations of target ranges to confirm satisfactory levels of obtained solutions	Need complex procedure to calculate LPP weight
Sensitivity analysis	Change mathematical weight among criteria	Change values of ε_2 and ε_3	Change combinations of target ranges	Change desirability ranges for each criterion to recalculate LPP weight
Formulation of transposed original objective functions	-	$f_2(x) \geq \varepsilon_2$ $f_3(x) \leq \varepsilon_3$	$f_1(x) \leq g_1^t$ $f_1(x) + (g_1^t - g_1^s)(d_1^- - d_1^+) = g_1^s$ $f_2(x) \geq g_2^t$ $f_2(x) + (g_2^s - g_2^t)(d_2^- - d_2^+) = g_2^s$ $f_3(x) \leq g_3^t$ $f_3(x) + (g_3^t - g_3^s)(d_3^- - d_3^+) = g_3^s$ $d_1^+ \leq d$ $d_2^- \leq d$ $d_3^+ \leq d$ $d_1^+, d_1^-, d_2^+, d_2^-, d_3^+, d_3^- \geq 0$	$f_1(x) - d_{1s}^+ = t_{1(s-1)}^+ \quad s = 2,3,4,5$ $f_1(x) \leq t_{15}^+$ $f_2(x) - d_{2s}^- = t_{2(s-1)}^- \quad s = 2,3,4,5$ $f_2(x) \geq t_{25}^-$ $f_3(x) - d_{3s}^+ = t_{3(s-1)}^+ \quad s = 2,3,4,5$ $f_3(x) \leq t_{35}^+$ $d_{is}^+, d_{is}^- \geq 0; \quad i = 1,2,3; \quad s = 2,3,4,5$

2.1.2 Goal programming

Goal programming is classified into two variants (Ilgin, Gupta and Battaïa, 2015). The first one is lexicographic or preemptive goal programming while the second one is termed weighted or non-preemptive goal programming (Ilgin, Gupta and Battaïa, 2015). The preemptive goal programming requires a decision maker to assume that all goals can be clearly prioritized, so that satisfying goals with a higher priority should be conducted more important than a lower priority goal (Ilgin, Gupta and Battaïa, 2015). Non-preemptive goal programming can seek a solution that all goals should be pursued simultaneously by setting mathematical weights based on decision maker’s relative importance to form a single utility function that is optimized (Ilgin, Gupta and Battaïa, 2015).

However, the determination of the proper priority level for a given objective or mathematical weight is difficult since the decision maker in the problem may not order and assign priorities to problem objectives in manner directly compatible with the goal programming model (Ignizio, 1976; Lee, 1972). To overcome these issues, Fushimi, Fukukawa and Yamaguchi (1987) developed goal vector method by goal programming (GP). GP procedure is consisted of 9 steps as shown in Fig. 2.1.One of the advantages of this method is that a decision maker do not have to determine priorities or mathematical weight among criteria. Instead of deterring priorities or allocating mathematical weight to reflect preferences of a decision maker, GP introduces tolerable and sufficient levels set by the decision maker. The tolerable level is defined as a level, where a decision maker is eager to achieve at least, in Fushimi, Fukukawa and Yamaguchi (1987). By setting only sufficient and tolerable levels for each goal, GP can evaluate different objective functions easily, even though the functions have different scales or units, such as the environmental loads and costs. Moreover, GP can seek different Pareto optimal solutions by changing only the target ranges for each criterion.

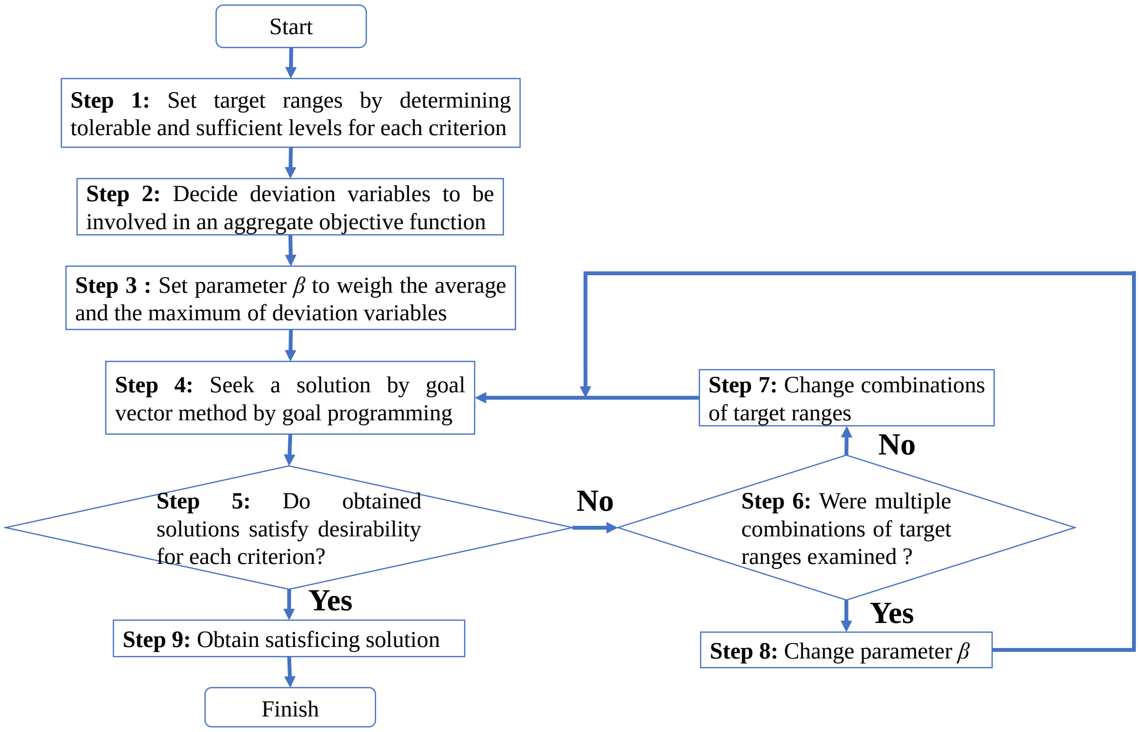

Figure 2.1 GP procedure

According to Kinoshita et al. (2016), in case of the bi-objective disassembly parts selection by GP, the target ranges of recycling cost should be fixed, while one of the recycling rate or CO_2 saving should be changed to 10 patterns to obtain satisficing solutions. Kinoshita et al. (2016) demonstrated relationships between the number of solutions and target ranges the multiple types of assembly products such as a cell phone, computer and vacuum cleaner. The detailed explanations for setting sufficient and tolerable levels are as follows:

The tolerable level of the recycling cost was set the sum of the positive recycling cost of each part, while sufficient level of one was set the sum negative recycling cost of each part. The parts with positive recycling cost were difficult to earn profit by selling recycled material recycling due to higher disassembly cost. On the other hand, the parts with negative one could earn profit from the material recycling due to higher sale revenue of the recycled materials. That is, the target ranges of the recycling cost was set to be minimized as much as possible.

With respect to the target ranges of the recycling rate, the tolerable and sufficient levels of one were changed based on dividing the feasible range of the total recycling rate defined as 0-100% equally. That is, these 10 patterns should be prepared to obtain satisficing solutions for recycling rate or CO_2 saving rate in the disassembly parts selection as follows: 1) 0-100%, 2) 0-50%, 3) 50-100%, 4) 0-33%, 5) 33-66%, 6) 66-100%, 7) 0-25%, 8) 25-50%, 9) 50-75%, 10)75-100%.

Therefore, the target ranges of the recycling cost should be fixed, while one of the recycling rate or CO_2 saving rate should be changed to 10 ranges to obtain a satisficing solution in the bi-objective disassembly parts selections.

2.1.3 Linear physical programming

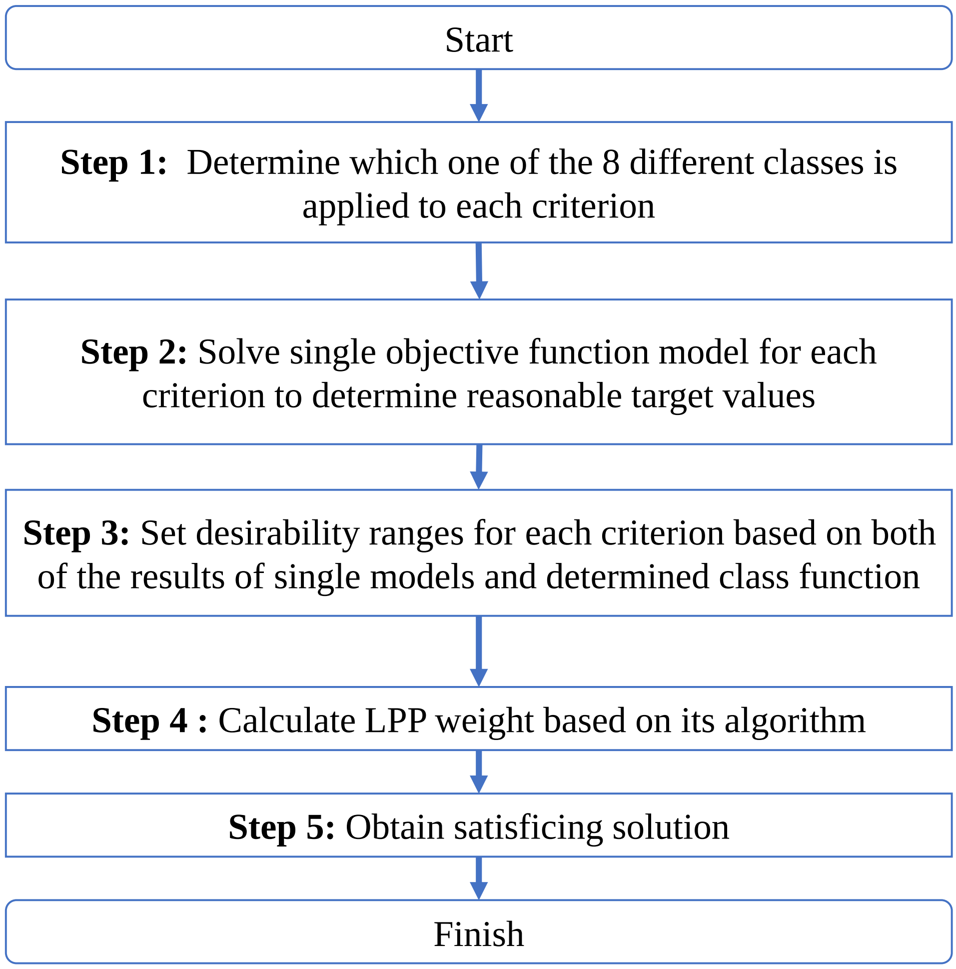

Figure 2.2 LPP procedure

The LPP procedure is consisted of 5 steps as shown in Fig. 2.2. An advantage of LPP is that it removes a DM from the weight allocation process (Ondemir and Gupta, 2014b). Instead of using a weight allocation process, in LPP, the DM is required to express his/her preference for each criterion by using four different classes, each of which has hard and soft classes (Messac, Gupta and Akbulut, 1996). The hard classes include Class-1H "Must be smaller," Class-2H "Must be larger," Class-3H "Must be equal," and Class-4H "Must be in range" (Messac, Gupta and Akbulut, 1996). The criteria belonging to the hard classes have only acceptable and unacceptable ranges, and thus, can be expressed with simple mathematical constraints.

In contrast, the soft classes include Class-1S "Smaller is better," Class-2S "Larger is better," Class-3S "Value is better," and Class-4S "Ranges better" (Messac, Gupta and

Akbulut, 1996). The criteria belonging to the soft classes are required to set 6 different desirability ranges for evaluation simultaneously by using an aggregate objective function. Figures 2.3 to 2.6 show the LPP soft class function regions for a generic *p*th objective, where the horizontal axis represents the value of criterion f_p, while the vertical axis represents the value of class function z^p (Joshi and Gupta, 2019). The 6 desirability ranges of each soft class, namely "ideal", "desirable", "tolerable", "undesirable", "highly undesirable", and "unacceptable" are set by the DM, while the values of class function z^p are calculated using the LPP weight algorithm. As illustrated in figures 2.3 to 2.6, the value of class function z^p in each type of soft classes decreases as the value of objective p approaches an ideal range.

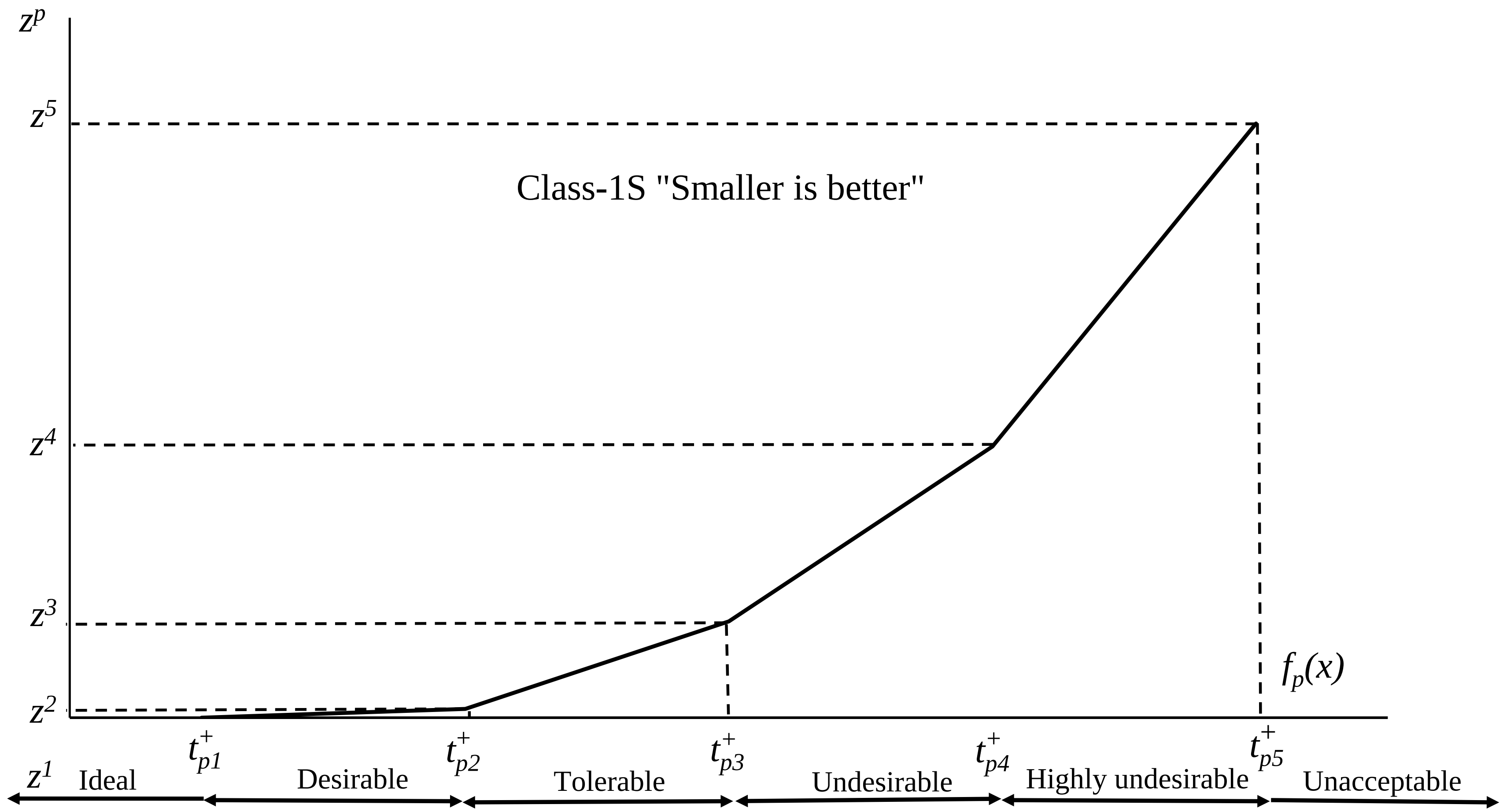

Figure 2.3 LPP soft class function regions for the generic *p*th objective: case of Class-1S “Smaller is better”

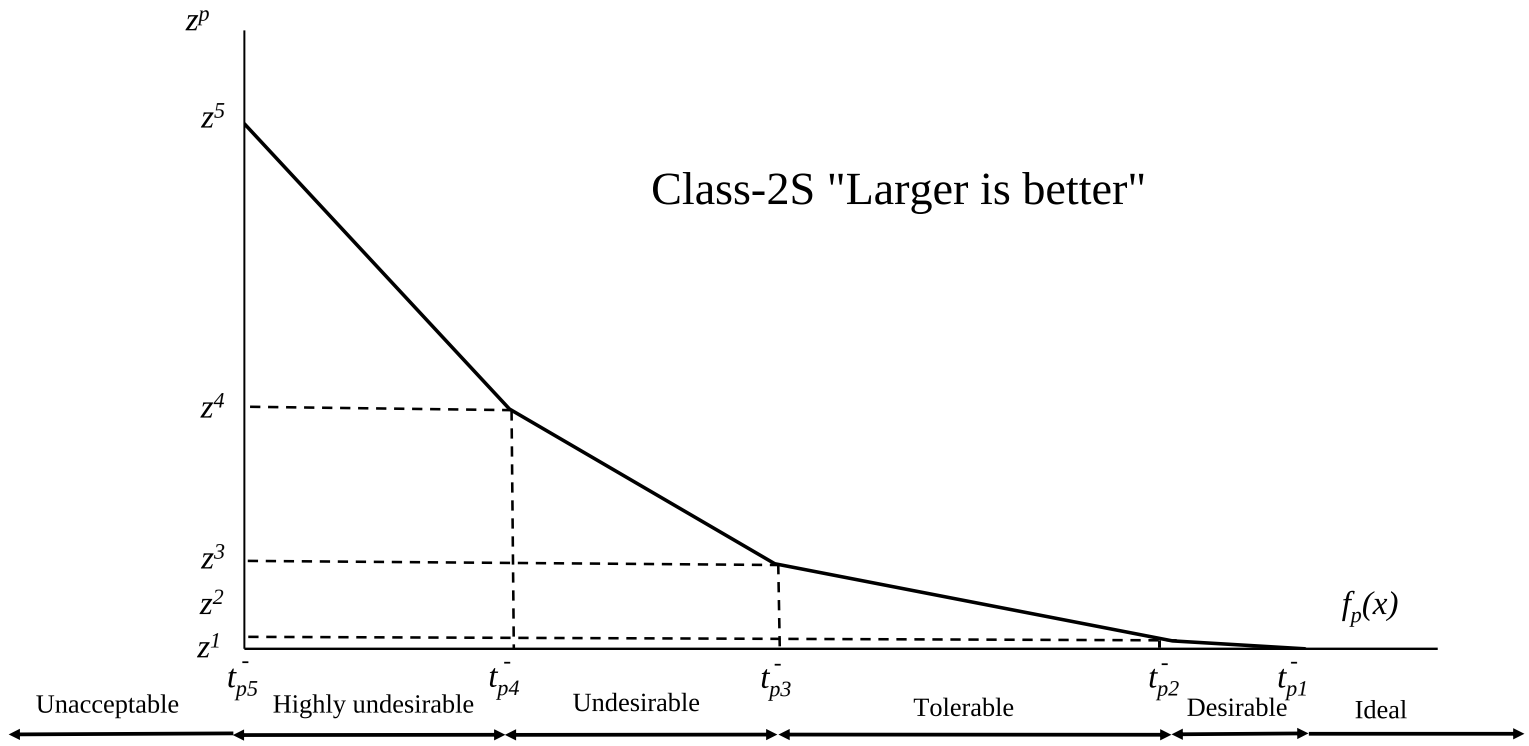

Figure 2.4 LPP soft class function regions for the generic *p*th objective: case of Class-2S "Larger is better"

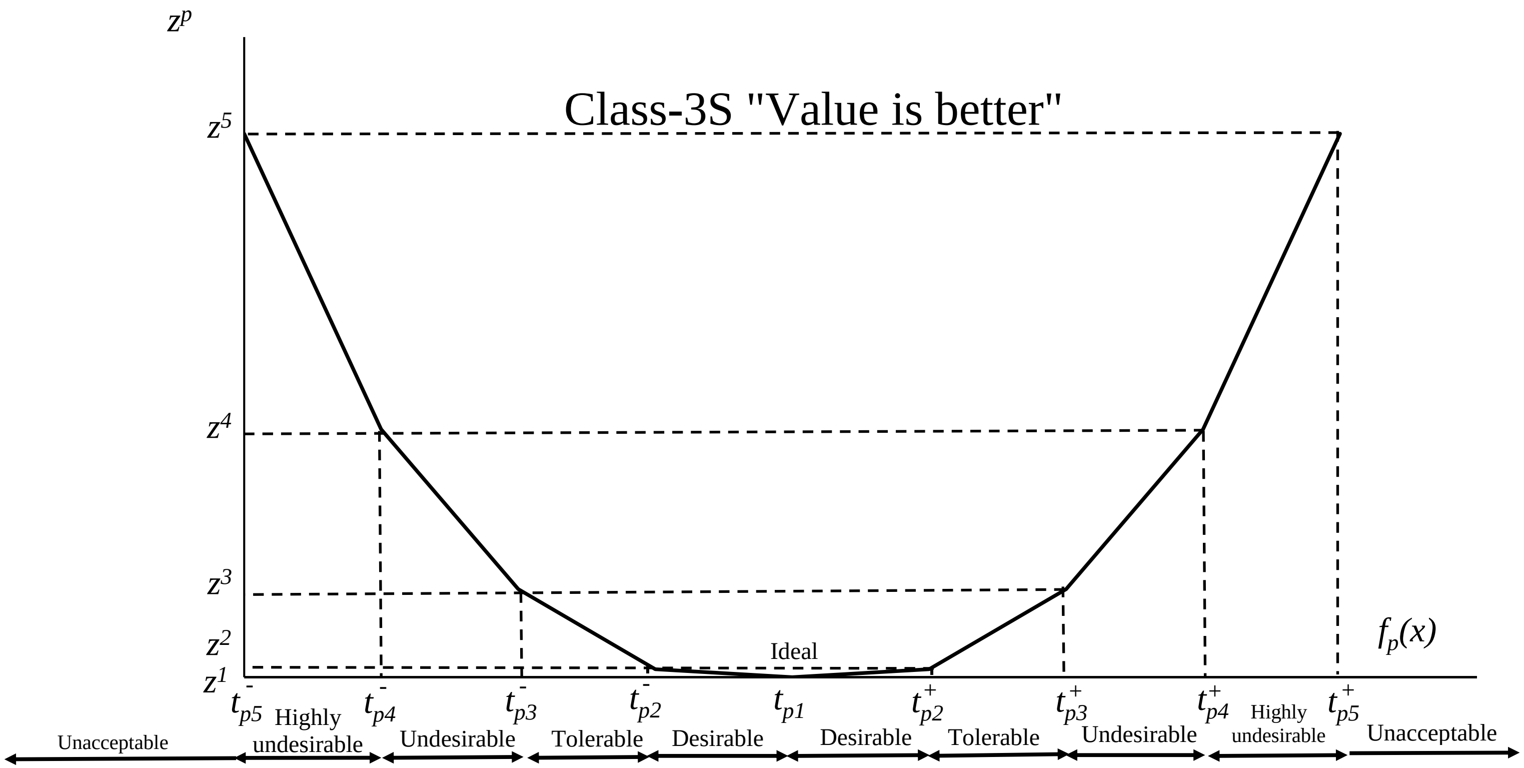

Figure 2.5 LPP soft class function regions for the generic *p*th objective: case of Class-3S “Value is better”

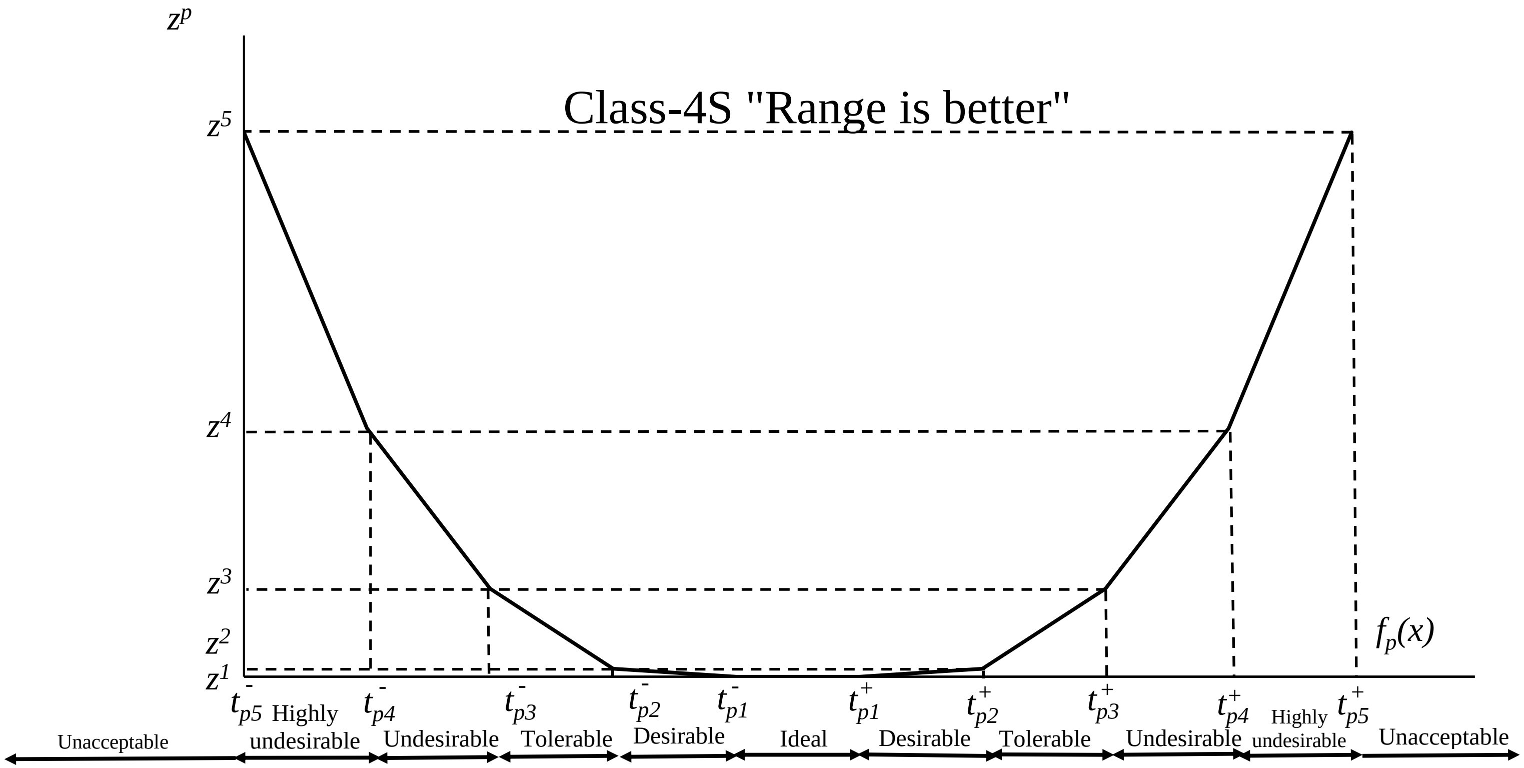

Figure 2.6 LPP soft class function regions for the generic *p*th objective: case of Class-4S “Range is better

The LPP weight algorithm is operated using an implied inter-criteria heuristic rule, called one vs. others criteria rule (OVO rule), where the LPP weight algorithm determines the weight required to improve the worst criteria first (Messac, Gupta and Akbulut, 1996). The detailed procedures of the LPP weight algorithm based on the OVO rules is described in Fig.2.7. The LPP weight algorithm is consisted of 9 steps as shown in Fig. 2.7. The LPP weight algorithm can be used to define the value of class functions z^s (s=1,2,3,4,5)based on the preference ranged defined by the DM (Messac， 2015). The overview of the LPP weight algorithm is overviewed as follows:

Step I: Initialize the parameters to calculate LPP weight.
Step II: Calculate LPP weight parameter of pth criterion.
Step III: Calculate sth LPP weight of pth criterion.
Step IV: Evaluate the parameters for LPP weights using Eqs. (2.1)-(2.6).
Step V: If $\widetilde{w}_{min}$ is less than 0.01, go to step VI. Otherwise go to step VII.
Step VI: Increase β to recalculate the LPP weight and back to step II.
Step VII: Repeat steps III, IV, and V until s=5.
Step VIII: Repeat steps II, III, IV, V, VI, and VII until all LPP weights are calculated.
Step IX: Finish calculation of LPP weights

Then, the LPP weight calculated using its algorithm reflects both desirability ranges set by the DM and OVO rule. To evaluate different criteria simultaneously, objective functions are transposed as constraints with positive/negative deviation variables from the sth limit of objective p d_{ps}^{+}/d_{ps}^{-} and the positive/negative sth limit of objective p t_{ps}^{+}/t_{ps}^{-}. By using the calculated LPP weight and positive/negative deviation variables, an aggregate objective function can evaluate all criteria of the soft classes simultaneously to seek one solution satisfying the criteria.

Regarding to the decision support model for material selection and multi-criteria disassembly production planning in DTO system, it is difficult to grasp the feasible maximum and minimum values of each criteria in contrast to the bi-objective disassembly parts selections since both of decision makings involve the decision variables with 2 dimensions. As one of the methods to set reasonable desirability ranges, Kongar and Gupta (2009) suggested to solve single models for each criterion to determine reasonable desirability ranges. Therefore, it is recommended to solve the MCDM problem as single objective models for each criterion firstly to know feasible maximum or minimum value of the criterion. After solving the single objective models, the desirability ranges should be set based on the results.

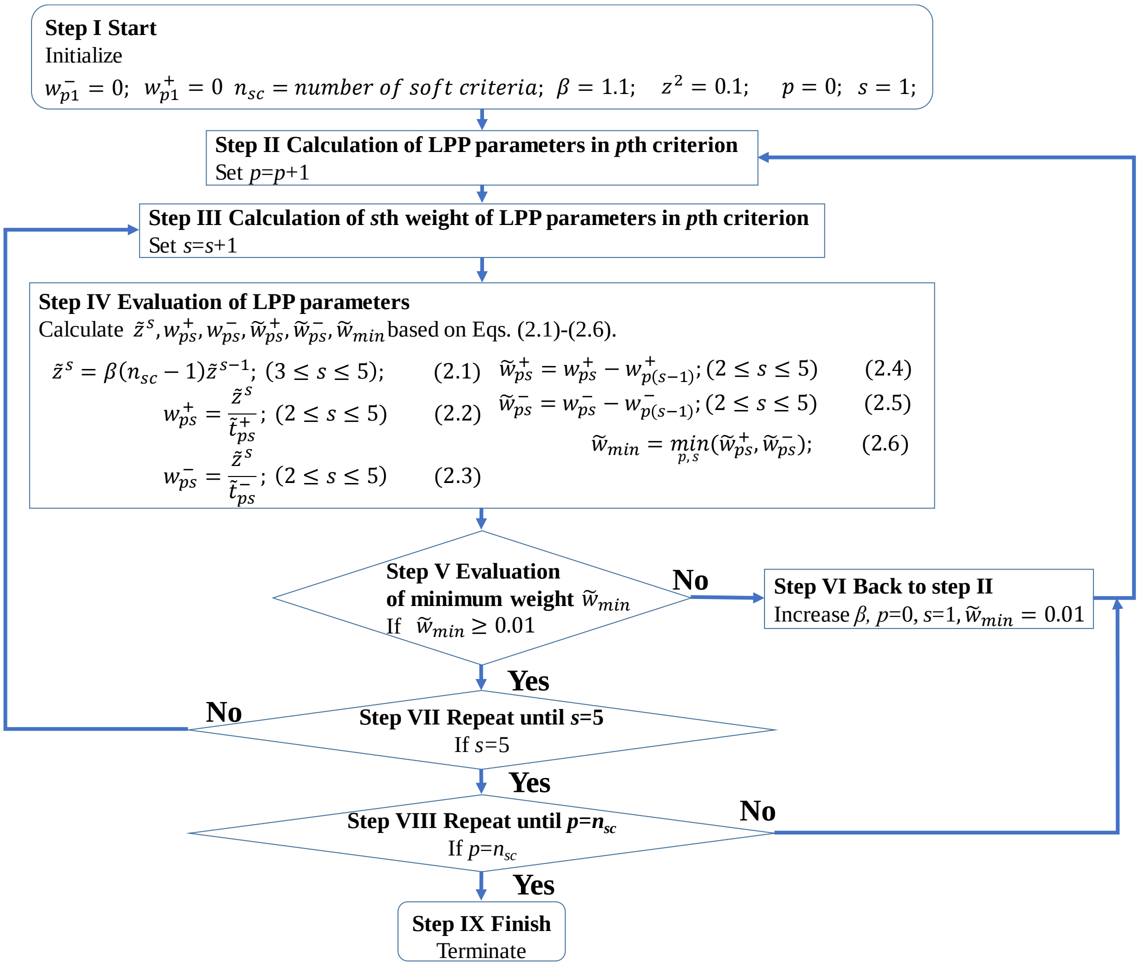

Figure 2.7 Flowchart of LPP weight algorithm

Notation of the LPP weight algorithm in Fig. 2.3

n_{sc}	:	Number of soft criteria
β	:	Convexity parameter (β>1.1)
p	:	Index of criteria; p=1, …, n_{sc}
s	:	Index of criteria; (1≤s≤5)
t_{ps}^{+}/t_{ps}^{-}	:	Target value set by a DM
$\tilde{t}_{ps}^{+}/\tilde{t}_{ps}^{-}$	:	Difference between targets set by a DM (2≤s≤5)
$\tilde{z}^s$	:	Difference between values of class functions z^s and z^{s-1} (2≤s≤5)
w_{ps}^{+}/w_{ps}^{+}	:	Magnitude of the slope of the class function
$\tilde{w}_{ps}^{+}/\tilde{w}_{ps}^{-}$	:	LPP weight calculated based on its algorithm (2≤s≤5)
$\tilde{w}_{min}$	:	Minimum LPP weight

2.2 Databases to estimate recycling rate, CO_2 emissions, and procurement/assembly/recycling costs

In section 2.1, the solving methods for multi criteria decision making (MCDM) problems are introduced. In addition to those MCDM techniques, information for each part listed on a bill-of-materials (BOM) is required to conduct the proposed decision makings. A BOM lists all subassemblies, parts, raw materials, components, and bulk products (Institute of Industrial and Systems Engineers), and also plays an important role in assembly and material requirement planning (MRP) (Nof, Wilhelm and Warnecke, 1997). In the case of a disassembly design methods for components reuse and material recycling, the recyclable weight, CO_2 emissions, and the costs for each part are required as input data. Table 2.2 shows a BOM with recyclable weight, CO_2 emissions and costs in a case of vacuum cleaner. To estimate recyclable weight, CO_2 emissions and costs, different types of databases are required. This section provides the 4 different databases to estimate the environmental and economic indices. Subsections 2.1 to 2.1 explains each databases.

Table 2.2 BOM with recyclable weight, CO_2 emissions and costs in case of vacuum cleaner

No.	Part name	Material type	Unit weight [g]	Total weight [g]	Procurement cost [yen]	Assembly cost	Recycling cost	Recyclable weight [g]	CO_2 emissions [g-CO_2eq]
1	Wheel	PP	9.44	18.88	2.62	26.68	21.77	18.88	18.05
2	Wheel stopper	PP	2.47	4.94	0.68	20.00	20.06	4.94	4.72
3	Upper nozzle	PP	56.33	56.33	7.81	10.00	17.49	56.33	53.86
4	Lower nozzle	PP	41.86	41.86	5.80	10.00	17.49	41.86	40.02
5	Nozzle	PP	33.70	33.70	4.67	10.00	17.49	33.70	32.22
6	Right handle	PP	48.93	48.93	6.78	28.33	13.37	48.93	46.78
7	Switch	PVC	4.65	4.65	0.58	26.73	13.37	4.65	4.02
8	Left handle	PP	51.70	51.70	7.16	10.60	17.49	51.70	49.43
9	Left body	PP	201.97	201.97	27.99	81.07	36.51	201.97	193.10
10	Right body	PP	195.08	195.08	27.03	10.54	17.49	195.08	186.51
11	Dust case cover	PMMA	36.57	36.57	9.64	10.00	17.49	36.57	66.52
12	Mesh filter	Cloth/Fiber	18.45	18.45	59.90	10.00	18.41	0.00	390.38
13	Connection pipe	Al/Al alloy	47.17	47.17	10.12	46.07	17.31	47.17	39.85
14	Dust case	PMMA	175.69	175.69	46.32	10.00	17.49	175.69	319.59
15	Exhaust tube	PVC	32.04	32.04	4.01	10.00	17.49	32.04	27.67
16	Upper filter	Cloth/Fiber	17.74	17.74	57.59	10.00	18.37	0.00	375.36
17	Lower filter	PP	29.33	29.33	4.06	10.00	17.49	29.33	28.04
18	Protection cap	ABS	24.42	24.42	4.79	10.00	17.49	24.42	33.03
19	Motor	Motor	310.73	310.73	11208.93	10.00	9.72	279.70	29465.72
20	Rubber of outer frame of fan	Rubber	22.85	22.85	5.56	12.00	18.63	0.00	50.44
21	Outer frame of fan	Al/Al alloy	55.11	55.11	11.82	28.73	8.96	55.11	46.55
22	Lower fan	PP	15.08	15.08	2.09	10.00	17.49	15.08	14.42
23	Fan	Al/Al alloy	62.10	62.10	13.32	10.00	12.52	62.10	52.46
	Total			1505.32	11529.29	420.75	401.39	1415.25	31538.73

2.2.1 Census of manufactures

The census of manufactures lists total volume of produced materials and total purchased amount of materials (Ministry of Economy, Trade and Industry, Census of Manufactures). Then, the unit material price is taken from the census of manufactures by dividing the total purchased amount by production volume (Yoshizaki et al, 2016). Similar to Yoshizaki et al. (2016), the procurement cost can be estimated by multiplying the weight by the unit material price taken from the census of manufacture.

2.2.2 Assembly Reliability Evaluation Method (AREM)

Assembly Reliability Evaluation Method (AREM) is software developed by Hitachi Ltd. to estimate the respective assembly cost for each part by inputting assembly tasks, length and weights (Suzuki et al., 2003; Ueno et al., 2004). Assembly cost is estimated using AREM. According to AREM, the assembly cost depends on assembly tasks, length and weights of the part. That is, the assembly cost is not influenced directly by changing the material types. However, the assembly cost is changed if the part weight becomes much heavier by adopting alternative materials.

2.2.3 Recyclability Evaluation Method (REM)

Recyclability Evaluation Method (REM) is also software developed by Hitachi Ltd. By using REM, recyclable weight and recycling costs can be estimated (Hiroshige, Nishi and Ohashi, 2001; Hitachi Ltd.). Recycling cost depends on disassembly tasks, material types, and weights of each part. On the other hand, the recyclable weight for each part is depend on its material type and weight. The recycling cost consists of disassembly cost, disposal cost, landfill cost, and sales of materials. The recycling cost can be a negative value (=positive profit) when the sales revenue from recovered materials is higher than the sum of disassembly, disposal, and landfill costs. Thus, the heavier parts made of metals such as Al/Al alloy and magnesium can be expected to generate profit through higher sales revenue from recovered materials.

The recycling rate for each part is defined as the ratio of recyclable weight compared with the whole product's weight based on the REM (Hiroshige, Nishi and Ohashi, 2001; Hitachi, Ltd.).

Hence, maximizing the total recycling rate by disassembly parts selection contributes to minimizing the disposal weight. In the case of a certain part made from materials that are difficult to recycle, the recycling rate becomes 0%. For example, the recycling rate for parts made of rubber or cloth/fiber becomes 0%. Thus, the disassembly for all parts does not always achieve a 100% recycling rate because of the nature of the materials and current technological/economic restrictions. The maximum achievable recycling rate is decided when a material is selected during a product's design phase.

2.2.4 Life cycle inventory database

Life Cycle Inventory (LCI) database has been developed to provide representative unit process data at national and regional levels to measure the greenhouse gas (GHG) emissions, including CO_2 emissions, of a wide range of industries (Sugiyama et al., 2005). According to the LCI database, CO_2 emissions in the material production phase also depend on the type of material and the weight (Itsubo Laboratory; Yoshizaki et al., 2016). Yoshizaki et al. (2016) proposed an estimation method for material-based CO_2 emissions using the LCI database with these I/O tables in China and Japan (Itsubo, N. Laboratory). By using the method proposed in Yoshizaki et al. (2016), CO_2 emissions in the material production phase can be calculated by matching each part's material types in the assembly products.

To measure the saved CO_2 volumes in the disassembly production, CO_2 saving rate is used instead of CO_2 volumes. The CO_2 saving rate for each part can be defined as the volume of CO_2 that can be reduced compared with the total CO_2 volume for the whole product if recycled material is used instead of virgin material (Igarashi et al., 2014). Thus, maximizing the CO_2 saving rate is considered to minimize additional CO_2 emissions from virgin material production.

3. Decision Support Model for Material Selection

This chapter proposes a decision support model for material selection by linear physical programming (LPP) in order to examine the effects on the procurement, assembly and recycling costs and environmental loads. First, the alternative material selection is explained and formulated as a multi criteria decision making problem. Next, LPP procedures are applied to the alternative material selection to seek the alternatives with lower costs and environmental loads. Finally, a case study is conducted based on the different scenarios, and is discussed in terms of the selected materials, the cost and environmental loads.

3.1 Overview of decision support of material selection

Materials for assembly products are selected in the product design phase to meet a wide range of desirable properties such as density strength, elasticity creep, ductility, hardness, and toughness (Holloway, 1998). Even though vast amounts of data would be needed to take all aspects of materials into consideration (Sapuan, 2001), materials are traditionally selected by applying trial and error or using expert experiences (Rahman, 2012). In addition to the functions of parts and products, economic factors such as procurement and assembly costs and weights also depend on material types. Moreover, material selection is the initial stage of the design process (Sapuan, 2001), which means that it affects the supply chain network since parts suppliers are changed based on procurement costs as the materials selected in the product design phase are changed. Product design is one of the constraints for logistics functions that determine the supply chain (Fine, Golany and Naseraldin, 2005).

Even though material types selected in the product design phase are one of the most important factors regarding recycling, it is difficult for product designers to consider environmental aspects because they already have to consider many other aspects such as cost and parts/product functions. Moreover, these desired properties are often in conflict with decisive factors and have trade-off relationships (Chan and Tong, 2007). Therefore, a decision support tool is required to enable product designers to consider the whole product life cycle and recycling aspects.

3.2 Procedures of proposed decision support model for material selection

Figure 3.1 shows decision support model for material selection by linear physical programming (LPP). The alternative material selection procedure consists of 5 steps. In step 1, bottleneck parts that impede economical material recycling are identified using a bill-of-materials (BOM). To promote environmentally friendly and economical material recycling, step 1 also selects candidate alternative materials. Step 2 estimates the procurement, assembly, and recycling costs, recyclable weights and CO_2 emissions using a 3D-CAD model, census of manufacturers, AREM, REM, and LCI database. Step 3 formulates multi-criteria alternative material selection using LPP. To obtain solutions that satisfy all criteria simultaneously, step 4 sets desirability ranges for each criterion to calculate mathematical weight based on LPP weight algorithm. Finally, the obtained solutions are evaluated to ascertain whether they satisfy the criteria of product designers in step 5. A detailed explanation is presented using a product example in section 3.4.

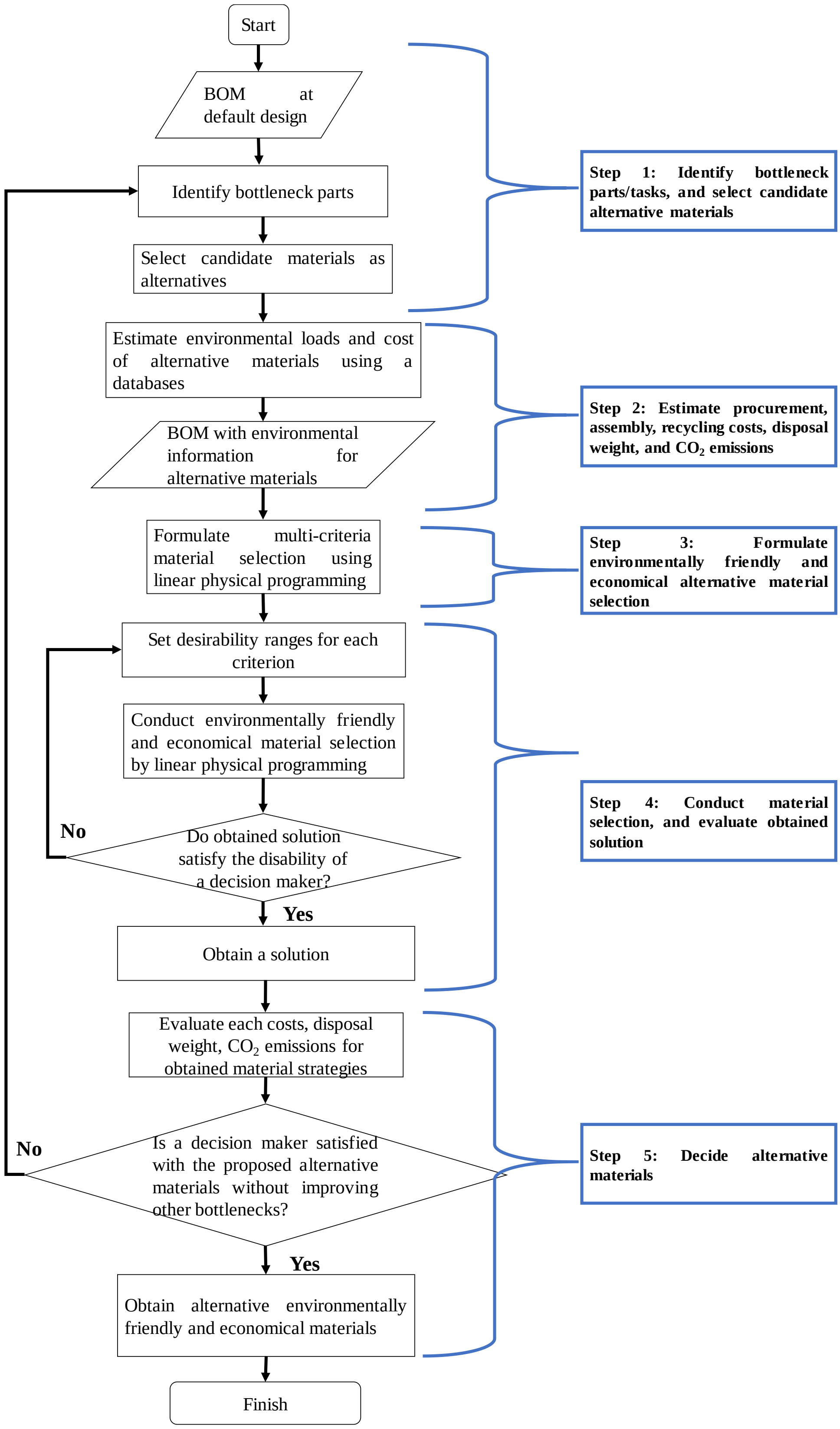

Figure 3.1 Decision support model for material selection using linear physical programming

3.3 Notation and formulation

This study proposes a decision support model for material selection for minimizing costs, disposal weight and CO_2 emissions using LPP. Each candidate material has different procurement, assembly, recycling costs, recyclable weight and CO_2 emissions. By evaluating not only these costs but also the disposal weight and CO_2 emissions simultaneously, alternative environmentally friendly and economically materials are selected.

A summary of the notations used in this study is presented below:

J	:	Set of parts/tasks
M	:	Set of materials
j	:	Index of parts
m	:	Index of materials
pc_{mj}	:	Procurement cost of material *m* at part *j*
ac_{mj}	:	Assembly cost of material *m* at part *j*
rc_{mj}	:	Recycling cost of material *m* at part *j*
r_{mj}	:	Recyclable weight of material *m* at part *j*
w_{mj}	:	Weight of material *m* at part *j*
e_{mj}	:	CO_2 emissions of material *m* at part *j*
α_a/α_r	:	Coefficient of assembly/recycling costs
pm_{mj}	:	Parameter; 1 if material *m* for part *j* is available for alternative design, otherwise 0
TC	:	Total cost
DW	:	Total disposal weight

E : Total CO_2 emissions

x_{mj} : Binary value; 1 if material m for part j is selected, otherwise 0

t_{is}^{+}, t_{is}^{-} : sth criterion of ith goal; ($1 \le s \le 5$)

d_{is}^{+}, d_{is}^{-} : Deviational variable of the ith goal from sth range intersection; ($2 \le s \le 5$)

$\tilde{w}_{is}^{+}, \tilde{w}_{is}^{-}$: Deviation weight of ith goal from sth range; ($2 \le s \le 5$)

The proposed material selection has 3 different objective functions including minimizing costs, minimizing disposal weight and minimizing CO_2 emissions as shown in Eqs. (3.1), (3.2) and (3.3). The decision variable is only x_{mj}, which represents selected material m at part j.

$$TC = \sum_{m \in M} \sum_{j \in J} \left(pc_{mj} + \alpha_a ac_{mj} + \alpha_r rc_{mj}\right) x_{mj} \rightarrow Min \tag{3.1}$$

$$DW = \sum_{m \in M} \sum_{j \in J} \left(w_{mj} - r_{mj}\right) x_{mj} \rightarrow Min \tag{3.2}$$

$$E = \sum_{m \in M} \sum_{j \in J} e_{mj} x_{mj} \rightarrow Min \tag{3.3}$$

The alternative material for each part j can be selected from the candidate material m as shown in Eq. (3.4). The Eq. (3.5) ensures that only one alternative or default material is selected for each part j.

s.t.

$$x_{mj} \le pm_{mj} \qquad \forall j \in J, \forall m \in M \tag{3.4}$$

$$\sum_{m \in M} x_{mj} = 1 \qquad \forall j \in J \tag{3.5}$$

To solve the multi-objective alternative material selection by using LPP, it is required to select classes and to set preference levels for each objective function.

All objective function as shown in Eqs. (3.1), (3.2) and (3.3) are belonged to the class-1S ("Smaller is better"), so that the 5 limitations are required to set the 6 ranges. To solve the alternative material selection by using LPP, the first objective function as shown in Eq. (3.1) is transposed to 2 constraints as shown in Eqs. (3.6) and (3.7).

$$TC - d_{1s}^{+} \leq t_{1(s-1)}^{+} \qquad s = 2,3,4,5 \tag{3.6}$$

$$TC \leq t_{15}^{+} \tag{3.7}$$

The deviation valuables d_{1s}^{+} (s=2,…,5) in Eq. (3.6) are positive values represented between the values of the total cost *TC* and the limitations $t_{1(s-1)}^{+}$. Eq. (3.7) ensures that the total cost *TC* is lower than one of the unacceptable range. Similar to the total cost *TC*, the other objective functions as shown in Eqs. (3.2) and (3.3) are transposed to the constraints as shown in Eqs. (3.8), (3.9), (3.10) and (3.11), respectively.

$$DW - d_{2s}^{+} \leq t_{2(s-1)}^{+} \qquad s = 2,3,4,5 \tag{3.8}$$

$$DW \leq t_{25}^{+} \tag{3.9}$$

$$E - d_{3s}^{+} \leq t_{3(s-1)}^{+} \qquad s = 2,3,4,5 \tag{3.10}$$

$$E \leq t_{35}^{+} \tag{3.11}$$

By using the calculated weights for each criterion, an aggregate objective function is formulated as follows:

$$\sum_{i=1}^{n_{sc}} \sum_{s=2}^{5} (\widetilde{w}_{is}^{-} d_{is}^{-} + \widetilde{w}_{is}^{+} d_{is}^{+}) \rightarrow Min \tag{3.12}$$

$$d_{is}^{+}, d_{is}^{-} \geq 0 \qquad i = 1, \dots, n_{sc}, s = 2,3,4,5 \tag{3.13}$$

All numerical experiments were conducted on the same desktop PC (Windows 10 with Intel(R) Core(TM) i5-9400 CPU@2.90GHz) by using a optimization solver named Numerical Optimizer (NTT DATA Mathematical System Inc.).

3.4 Numerical example

To illustrate a design example of the proposed decision support model for material selection, a vacuum cleaner is used as example product for the selection of alternative materials in this section.

3.4.1 Product and material selection problem

Table 2.2 shows BOM including the recyclable weight of the vacuum cleaner. The vacuum cleaner consists of 23 original parts and 7 different materials including polypropylene (PP), methacrylic resin (PMMA), vinyl chloride resin (PVC), polystyrene (ABS), Al/Al alloy, rubber, and cloth/fiber and motor. The total weight of the vacuum cleaner is 1505.32g. The PP is the heaviest material type and is used in 11 of 23 parts of the vacuum cleaner.

The assumptions of the proposed alternative material selection are as follows:

- Shapes and functions for each part and the whole product are not changed, only weights are changed as the material types are changed.
- It focuses on only material recycling (reuse, refurbish, etc. are not considered).
- Every part is made of one material.

3.4.2 Design example

This subsection explains the steps for the selection of alternative materials with material strategies as shown in Fig. 3.1 Steps 1 and 2 are preparation stages to produce the input data for the alternative material selection. However, steps 1 and 2 do not require knowledge about materials since the purpose of this selection is to provide the product designers with the effect on the costs, disposal weights and CO_2 emissions by examining alternative materials.

Step 1. Identify bottleneck parts and select candidate alternative materials

Step 1 identifies the bottlenecks for impeding recycling and selects candidate alternative materials. Here, the bottlenecks are considered as parts with heavier weight, made of difficult materials for recycling or higher CO_2 emissions. The material changes of heavier parts are expected to reduce procurement and recycling costs since these costs depend on the weight of parts largely. Moreover, another reason of identifying heavier weight as bottlenecks is that trade-off relationship of metals and plastics between procurement and recycling costs. Procurement cost of metals tends to be higher than that of plastics, while recycling cost of metals tends to be lower than that of plastics.

On the other hand, some materials are difficult for material recycling. For example, clothe/fiber and rubber are difficult for recycling. Then, these materials should be changed to other recyclable materials, so that the disposal weight is reduced. The disposal weight can be defined as the differences between weights and recyclable weights, and can be reduced by changing alternative materials.

Regarding to CO_2 emissions, it also depends on the material type. Then, by changing the material type with the higher CO_2 emissions, the total CO_2 emissions would be reduced. Therefore, parts with higher procurement or recycling costs, heavier disposal weight, or higher CO_2 emissions can be the bottleneck, and have a possibility to reduce the whole supply chain cost, disposal weight and CO_2 emissions simultaneously by changing only its materials.

Candidate alternative materials should be select from various types of materials including not only metals, and plastics but also glass, wood, fiber, etc. Since this study proposes a material selection method based on a mathematical model, one material is selected for each bottleneck part to satisfy the all preferences of costs, recyclable weight and CO_2 emissions set by a DM, although the candidate materials increase. It is better to select more candidate materials rather than less ones so as to the mathematical model tries to select suitable alternative materials for a DM's preferences.

(1) Higher recycling cost and heavier parts

From the BOM of the vacuum cleaner as shown table 2.2, the second and third heaviest parts are identified as parts #9 left and #10 right bodies made of PP. It is found that their disposal weights can become 0g. However, the recycling cost of #9 left body is 2.09 times higher than the average. Therefore, this is identified as one of the bottlenecks for impeding recycling due to it having the highest recycling cost. Moreover, the materials for #10 right body should be the same as those of #9 left body since the both parts are symmetrical. The recycling cost of the whole product in the case of the vacuum cleaner is expected to become lower than one in the default design by changing materials for the #9 left and # 10 right bodies.

(2) Non-recyclable materials and higher CO_2 emissions

The recyclable weights of parts made of cloth/fiber and rubber such as #12 mesh filter, #16 upper filter, and #20 rubber outer frame of fan are found to become 0g due to their material types. It is also revealed that the procurement cost and CO_2 emissions for #12 mesh filter and #16 upper filter are the second and third highest in the whole product. Thus, these 3 parts are identified as bottlenecks and disposal weights, procurement cost and CO_2 emissions can be reduced by selecting alternative materials from those used in the default design. Therefore, 5 bottlenecks have been identified that impede material environmentally friendly and cost-effective recycling.

After identifying the bottleneck parts, the candidate alternative materials are identified. To satisfy these demands, 8 different candidate materials consisting of 3 metals, 3 plastics, and 2 other materials, including aluminum, magnesium, iron, polypropylene, methacrylate resin, vinyl chloride resin, glass fiber, and carbon fiber are proposed as alternative materials.

Step 2. Estimate procurement/assembly/recycling cost, disposal weight and CO_2 emissions

Step 2 estimates procurement, assembly, and recycling costs, recyclable weights and CO_2 emissions for each candidate material by using databases and 3D-CAD model. It is assumed that shapes and functions for each part and the whole product are not changed, but only weights are changed as the material types are changed. The recyclable weight, CO_2 emissions and costs are estimated by using databases described in section 2.2. Table

3.1 shows a BOM including recycling cost and recyclable weight for candidate alternative materials. The weights of the materials are estimated using a 3D-CAD model.

Table 3.1 BOM with the results of the alternative material selection: case of a vacuum cleaner

No.	Material type	Part name	Total weight [g]	Procurement cost [yen]	Assembly cost	Recycling cost	Recyclable weight [g]	CO_2 emissions [g-CO2eq]	Default design	Results of material selection by LPP
1-9	Default	Left body	201.97	27.99	81.07	36.51	201.97	193.10	X	X
2-9	Aluminium	Left body	612.73	131.40	81.07	-12.50	612.73	517.61		
3-9	Magnesium	Left body	385.79	77.16	81.07	-25.51	385.79	303.94		
4-9	Iron	Left body	1792.79	73.79	100.46	22.34	1792.79	506.53		
5-9	Polypropylene	Left body	-	-	-	-	-	-		
6-9	Metacrylate resin	Left body	272.32	71.80	81.07	36.51	272.32	495.36		
7-9	Vinyl chloride resin	Left body	295.02	36.93	81.07	36.51	295.02	254.76		
8-9	Glass fiber	Left body	628.61	309.34	81.07	30.23	628.61	1692.50		
9-9	Carbon fiber	Left body	453.87	1473.53	81.07	36.51	0.00	9603.34		
1-10	Default	Right body	195.08	27.03	10.54	17.49	195.08	186.51	X	X
2-10	Aluminium	Right body	591.80	126.91	10.54	-29.86	591.80	499.93		
3-10	Magnesium	Right body	372.62	74.52	10.54	-42.13	372.62	293.56		
4-10	Iron	Right body	1731.57	71.27	12.91	3.80	1731.57	489.23		
5-10	Polypropylene	Right body	-	-	-	-	-	-		
6-10	Metacrylate resin	Right body	263.02	69.35	10.54	17.49	263.02	478.45		
7-10	Vinyl chloride resin	Right body	284.94	35.67	10.54	17.49	284.94	246.05		
8-10	Glass fiber	Right body	607.14	298.78	10.54	11.41	607.14	1634.69		
9-10	Carbon fiber	Right body	438.37	1423.21	10.54	17.49	0.00	9275.38		
1-12	Default	Mesh filter	18.45	59.90	18.45	18.41	0.00	390.38	X	
2-12	Aluminium	Mesh filter	27.52	5.90	18.45	15.28	27.52	23.25		
3-12	Magnesium	Mesh filter	17.32	3.46	18.45	14.71	17.32	13.65		X
4-12	Iron	Mesh filter	80.51	3.31	18.45	16.84	80.51	22.75		
5-12	Polypropylene	Mesh filter	9.07	1.26	18.45	17.49	9.07	8.67		
6-12	Metacrylate resin	Mesh filter	12.23	3.22	18.45	17.49	12.23	22.25		
7-12	Vinyl chloride resin	Mesh filter	13.25	1.66	18.45	17.49	13.25	11.44		
8-12	Glass fiber	Mesh filter	28.23	13.89	18.45	17.20	28.23	76.01		
9-12	Carbon fiber	Mesh filter	20.38	66.17	18.45	17.49	0.00	431.22		
1-16	Default	Upper filter	17.74	57.59	17.74	18.37	0.00	375.36	X	
2-16	Aluminium	Upper filter	26.47	5.68	17.74	15.37	26.47	22.36		
3-16	Magnesium	Upper filter	16.66	3.33	17.74	14.82	16.66	13.13		X
4-16	Iron	Upper filter	77.44	3.19	17.74	16.87	77.44	21.88		
5-16	Polypropylene	Upper filter	8.72	1.21	17.74	17.49	8.72	8.34		
6-16	Metacrylate resin	Upper filter	11.76	3.10	17.74	17.49	11.76	21.39		
7-16	Vinyl chloride resin	Upper filter	12.74	1.59	17.74	17.49	12.74	11.00		
8-16	Glass fiber	Upper filter	27.15	13.36	17.74	17.21	27.15	73.10		
9-16	Carbon fiber	Upper filter	19.60	63.63	17.74	17.49	0.00	414.71		
1-20	Default	Rubber of outerframe of fan	22.85	5.56	22.85	18.63	0.00	50.44	X	
2-20	Aluminium	Rubber of outerframe of fan	61.68	13.23	22.85	12.55	61.68	52.10		
3-20	Magnesium	Rubber of outerframe of fan	38.84	7.77	22.85	11.27	38.84	30.60		X
4-20	Iron	Rubber of outerframe of fan	180.48	7.43	22.85	16.04	180.48	50.99		
5-20	Polypropylene	Rubber of outerframe of fan	20.33	2.82	22.85	17.49	20.33	19.44		
6-20	Metacrylate resin	Rubber of outerframe of fan	27.41	7.23	22.85	17.49	27.41	49.86		
7-20	Vinyl chloride resin	Rubber of outerframe of fan	29.70	3.72	22.85	17.49	29.70	25.65		
8-20	Glass fiber	Rubber of outerframe of fan	63.28	31.14	22.85	16.85	63.28	170.38		
9-20	Carbon fiber	Rubber of outerframe of fan	45.69	148.34	22.85	17.49	0.00	966.75		

Step 3. Formulate environmentally friendly and economical alternative material selection

In step 3, the multi-objective environmentally friendly and economical alternative material selection is formulated as outlined in section 3.3.

Step 4. Conduct material selection and evaluate obtained solution

By using the estimated data in step 2, this section conducts the multi-objective material selection based on linear physical programming (LPP) procedures. To set reasonable desirability ranges, Kongar and Gupta (2009) suggested to solve single models for each criterion. Then, the material selection solved as single objective models for each criterion firstly to know feasible maximum or minimum value of the criterion. Table 3.2 shows the results of the single models of each criterion. Based on the results of minimum values of the criteria as shown table 3.2, each preference level of all objective functions belonged class-1S ("Smaller is better") is set to define 6 desirability ranges as shown in table 3.3. By using the desirability ranges in Table 3.3, the LPP weight algorithm calculate the weights of each criterion as shown in Table 3.4.

Table 3.2 Results of single models for each criterion

Objective function	Criteria		
	Total cost	Disposal weight [g]	CO_2 emissions [g-CO_2eq]
Min Total cost	290.06	0	654.867
Min Disposal weight	344.455	0	889.291
Min CO_2 emissions	317.431	0	416.054

Table 3.3 Desirability levels for costs, disposal weight and CO_2 emissions

Degree of desirability	Total cost	Disposal weight [g]	CO_2 emissions [g-CO_2eq]
Ideal	$\leqq$200	$\leqq$25	$\leqq$300
Desirable	(200, 250]	(25, 30]	(300, 500]
Tolerable	(250, 330]	(30, 50]	(500, 1000]
Undesirable	(330, 400]	(50, 70]	(1000, 2000]
Highly undesirable	(400, 500]	(70, 100]	(2000, 2500]
Unacccptable	$>$500	$>$100	$>$2500

Table 3.4 Calculated weights by using LPP weight algorithm:

	Total cost	Disposal weight	CO_2 emissions
$\tilde{w}^{+}_{i,2}$	0.700	7.000	0.175
$\tilde{w}^{+}_{i,3}$	1.059	0.035	0.106
$\tilde{w}^{+}_{i,4}$	6.321	21.246	0.284
$\tilde{w}^{+}_{i,5}$	14.657	47.512	3.982

Step 5. Conduct material selection and evaluate obtained solution

Table 3.5 shows results of alternative material selection. The results in table 3.5 indicates the total cost, disposal weight and CO_2 emissions for whole product. The aspiration levels of the total cost, disposal weights and CO_2 emissions become tolerable, ideal and desirable, respectively. The disposal weight and CO_2 emissions could be reduced 65% and 2% simultaneously with reduction of 0.78% total cost in the numerical experiments. The "X" in table 3.1 represent the selected alternative materials. From Table 3.1, it is found that magnesium is selected for other 3 parts such as #12 mesh filter, #16 upper filter and #20 rubber outer flame, while materials of #9 left and # 10 right bodies are not changed from one of default design.

Table 3.5 Results of alternative material selection

	Total cost		Disposal weight [g]		CO_2 emissions [g-CO2eq]	
	Value	Difference [%]	Value	Difference [%]	Value	Difference [%]
Default design	12351.43	-	90.07	-	31538.73	-
Material selection	12255.37	-0.78%	31.03	-65.55%	30779.92	-2.41%

3.5 Summary of decision support model for material selection

The decision support model for material selection was proposed to minimize costs, disposal weight and CO_2 emissions the using linear physical programming (LPP). The decision maker (DM) could obtain suggested materials by the decision support model with only expressing his/her desirability ranges for each criteria. The case was found that disposal weight and CO_2 emissions could be reduced 65% and 2% simultaneously with reduction of 0.78% total cost in the numerical experiments. Only PP and Magnesium were selected as alternatives even though 9 different materials were prepared for alternatives.

4 Bi-objective disassembly parts selection for recycling rate and cost using goal programming

In this chapter, a bi-objective disassembly parts selection for recycling rate and cost using goal vector method by goal programming (GP) is presented. This study applies GP to the environmentally friendly and economical disassembly parts selection instead of integer programming with the ε constraint method at stage 1 in (Igarashi, Yamada and Inoue, 2014). Section 4.1 overviews the bi-objective disassembly parts selection for recycling rate and cost using GP. Section 4.2 formulates the bi-objective disassembly parts selection using GP. A design example is illustrated in section 4.3 using a cell phone. In section 4.4, comparison of different assembly products and examination of between the number of target ranges and obtained solutions are conducted to clarify practical implications of the proposed model. Finally, section 4.5 summarizes the findings.

4.1 Overview of disassembly parts selection

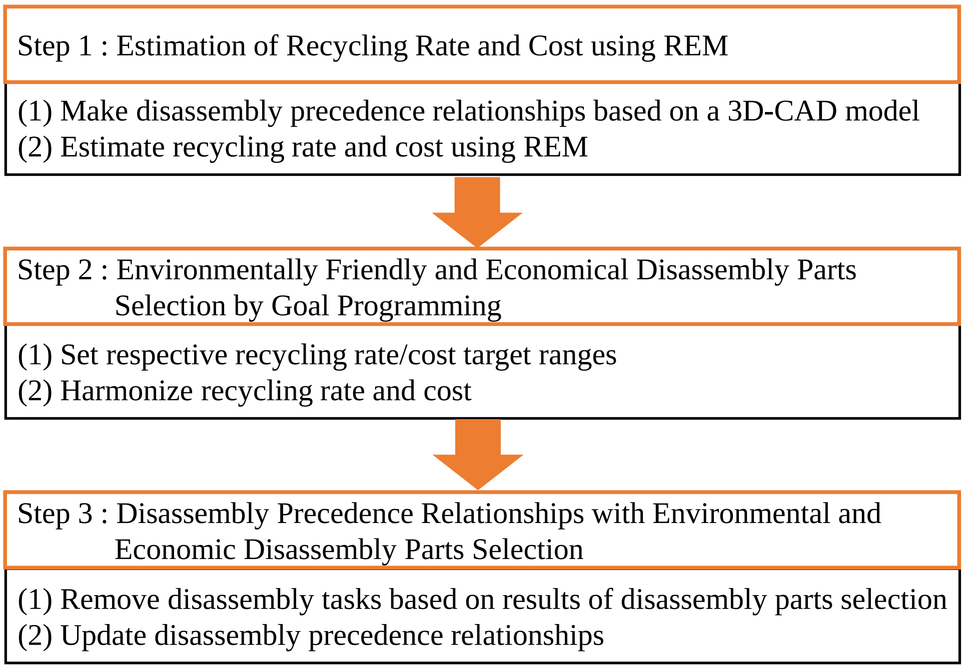

Figure 4.1 Overview for environmentally and economical disassembly parts selection including goal programming

Section 4.1 presents the design procedures of the bi-objective disassembly parts selection for recycling rate and cost. A proposed design procedures are consisted of 3 steps as shown in Fig. 4.1. In the step 1, the recycling rate and cost are estimated by using recyclability evaluation method (REM). Step 2 formulates the environmentally friendly and economical disassembly parts selection using GP. In the step 3, the precedence relationships are updated based on results of the environmental friendly and economical disassembly parts selection. Thus, detailed explanations of each step are developed as follows:

Step 1: Estimation of recycling rate and cost using REM

(1) Estimation recycling rate and cost using REM

Similar to (Igarashi, Yamada and Inoue, 2014), several real data from a 3D-CAD model, such as weights, materials and types of disassembly works, are used to estimate the recycling rate and cost by REM (Hitachi Ltd.; Hiroshige, Nishi and Ohashi, 2001) at Step 1. The REM (Hitachi Ltd.; Hiroshige, Nishi and Ohashi, 2001) is a method and software used to estimate disassembly times, recycling rate, recycling cost—including disassembly cost, disposal cost, sales of materials and landfill cost (Hitachi Ltd.; Hiroshige, Nishi and Ohashi, 2001)—by inputting weights, materials, and types of disassembly tasks for each part. That is, based on real data such as weights, materials and types of disassembly works from the 3D-CAD model, the recycling rate and cost are estimated by the REM (Hitachi Ltd.; Hiroshige, Nishi and Ohashi, 2001).

(2) Make disassembly precedence relationships based on 3D-CAD model

According to (Igarashi, Yamada and Inoue, 2014), by using a 3D-CAD model, a product structure is grasped, and its disassembly precedence relationships are created.

Step 2: Environmentally friendly and economical disassembly parts selection using goal programming

(1) Set respective recycling rate/cost target ranges.

This environmentally friendly and economical disassembly parts selection has 2 criteria: minimizing the recycling cost and maximizing the recycling rate.

In general, it is very difficult for management designers to set desirable targets for each criterion. In contrast, it is easier to set target ranges such a tolerable to sufficient level than to set a direct desirable target (Fushimi, Fukukawa and Yamaguchi, 1987) Also, it is difficult to prioritize goals because decision-makers are eager to achieve multiple croteroa at the same time (Fushimi, Fukukawa and Yamaguchi, 1987). Hence, this study sets target ranges for each goal, which enables us to seek solutions while satisfying 2 criteria simultaneously.

The proposed disassembly parts selection by GP enables us to set as tolerable total recycling cost C_0, sufficient total recycling cost C_s, tolerable total recycling rate R_0 and sufficient total recycling rate R_s. One of the reasons for this is that GP requests to set each range of the target goals.

(2) Harmonize recycling rate and cost

Decision-makers often need to obtain not only the best solution but also other solutions in order to compare the solutions in terms of effectiveness and feasibility from the viewpoints not constructed in this optimization (Fushimi, Fukukawa and Yamaguchi, 1987). Therefore, the Pareto optimally solutions, which satisfy target ranges for each criterion, are here sought by changing the target ranges.

Step 3: Disassembly precedence relationships with environmentally friendly and economical disassembly parts selection

(1) Remove disassembly tasks based on results of disassembly parts selection

Canceled disassembly parts with the non-selective are removed from the old precedence relationships. It is assumed that all selected parts are manually disassembled for material recycling, and non-selected parts are broken and removed without recycling rate and cost.

(2) Update disassembly precedence relationships

The precedence relationships are updated based on the results of the environmentally friendly and economical disassembly parts selection in a manner similar to that used by (Igarashi, Yamada and Inoue, 2014).

4.2 Notation and formulation

Notation and formulation of the bi-objective disassembly parts selection using GP are described in this section.

A summary of the notations in this study is presented below:

i	:	Index for predecessors of part j with task j
j	:	Index of parts/tasks (j=1,2,…,N)
N	:	Number of parts
J	:	Set of parts/tasks
c_j	:	Recycling cost at part j
r_j	:	Recycling rate at part j
P_j	:	Set of tasks that immediately precede task j at part j
C	:	Total recycling cost
C_0	:	Tolerable total recycling cost
C_s	:	Sufficient total recycling cost
R	:	Total recycling rate
R_{max}	:	Recycling rate when all parts are disassembled
R_0	:	Tolerable total recycling rate
R_s	:	Sufficient total recycling rate
x_j	:	Binary value; 1 if part j is disassembled, else 0
d_1^+, d_1^-	:	Deviational variable between the total recycling costs C and sufficient recycling costs C_s

d_2^+, d_2^- : Deviational variable between the total recycling rate R and sufficient recycling rate R_s

d : Maximum deviational variable

β : Parameter to weigh the average and the maximum of d

RE : Recycling efficiency (= R / C)

This bi-objective disassembly parts selection has 2 objective functions: to minimize recycling cost C and to maximize recycling rate R as shown in Eqs. (4.1) and (4.2).

$$C = \sum_{j=1}^{N} c_j x_j \rightarrow Min \tag{4.1}$$
$$R = \sum_{j=1}^{N} r_j x_j \rightarrow Max \tag{4.2}$$

To solve this bi-objective problem, GP is applied as follows:

1. The first goal is to minimize total recycling cost *C*.

Total recycling cost C, including disassembly cost, sale of materials, disposal cost and landfill cost, is under tolerable total recycling cost C_0, aiming to reach sufficient total recycling cost C_s and obtained as Eqs. (4.3) and (4.4). The d_1^+ and d_1^- are positive and negative deviational variables that show differences in sufficient cost C_s. By minimizing d_1^+, total recycling cost C tries to reach sufficient total recycling cost C_s. (C_0 - C_s) is a coefficient that normalizes each goal. The first goal can be formulated as follows:

Goal: minimize d_1^+
Subject to:

$$C + (C_0 - C_s)(d_1^- - d_1^+) = C_s \tag{4.3}$$

$$C \leq C_0 \tag{4.4}$$

2. The second goal is to maximize total recycling rate *R*.

Total recycling rate R is greater than tolerable total recycling rate R_0, and aims to reach sufficient total recycling rate R_s as obtained in Eqs. (4.5) and (4.6). Similar to Eq. (4.3), the deviation variable d_2^+, d_2^- and the coefficient (R_s-R_0) are set. By minimizing d_2^-, total recycling rate R tries to reach sufficient total recycling cost R_s. The second goal can be formulated as follows:

Goal: minimize d_2^-

Subject to:

$$R + (R_0 - R_s)(d_2^- - d_2^+) = R_s \tag{4.5}$$

$$R \leq R_0 \tag{4.6}$$

Similar to (Igarashi, Yamada and Inoue, 2014), the constraint of precedence relationships among disassembly tasks is set as Eq. (4.7) based on (Nof, Wilhelm and Warnecke, 1997). Other constraint equation is obtained as Eq. (4.8).

$$x_j - x_i \leq 0 \quad i \in P_j \tag{4.7}$$

$$d_1^+, d_1^-, d_2^+, d_2^- \geq 0 \tag{4.8}$$

The whole objective function is obtained as Eqs. (4.9), (4.10) and (4.11). This study aims to minimize the average of the deviational variable, which represents the differences of the goal, total recycling rate/cost, and maximum deviational variable d. $\frac{d_1^+ + d_2^-}{2}$ means the average, and d means maximum of d_1^+ and d_2^-. β is a parameter to weigh the average and maximum of the deviational variable.

$$\beta \frac{d_1^+ + d_2^-}{2} + (1 - \beta)d \rightarrow \text{Min} \tag{4.9}$$

$$d \geq d_1^+ \tag{4.10}$$

$$d \geq d_2^- \tag{4.11}$$

By using the mathematical programming package developed by Numerical Optimizer (NTT DATA Mathematical System Inc.), the environmentally friendly and economical disassembly parts selection is optimized to harmonize the recycling rate and cost.

4.3 Design example of environmentally friendly and economical disassembly parts selection using goal programming: case of cell phone

This section adopts the cell phone (Igarashi, Yamada and Inoue, 2014) to the environmentally friendly and economical disassembly parts selection by GP.

4.3.1 Problem example

The cell phone has 12 original parts, and the whole recycling rate and cost are 80.14% (=R_{max}) and 89.40. The environmentally friendly and economical disassembly parts selection is performed based on the disassembly relationships, recycling rate and cost for each part.

In order to apply GP to the environmentally friendly and economical disassembly parts selection, this study requires the tolerable and sufficient levels to set target ranges for each goal at Step 2. In order to obtain the Pareto optimal solutions harmonizing the recycling rate and cost, the environmentally friendly and economical disassembly parts selection in this study is carried out by minimizing the recycling cost under the recycling rate of 3 patterns as follows:

- Pattern 1) All ranges from 0% to 100% (R_0=0, R_s=R_{max})
- Pattern 2) Division into 3 areas from 0% to 33% (R_0=0, R_s=R_{max}×33%), from 33% to 66% (R_0=R_{max}×33%, R_s=R_{max}×66%) and from 66% to 100% (R_0= R_{max}×66%, R_s=R_{max}),
- Pattern 3) Changing in increments of 10% from 0% to 10% (R_0=0, R_s=R_{max}×10%), from 10 % to 20% (R_0=R_{max}×10%, R_s=R_{max}×20%), …from 80% to 90% (R_0=R_{max}×80%, R_s=R_{max}×90%), and from 90 % to 100% (R_0=R_{max}×90%, R_s=R_{max}).

Pattern 1) "all ranges" means minimizing recycling cost and maximizing recycling rate, and we expect to find the best or near best recycling rate and cost coexistence solution. Pattern 2) division into 3 areas is expected to provide alternative solutions to compare with the pattern 1) all ranges. Pattern 3) changing in increments at 10% is set.

The recycling cost target range is set from a sum of negative cost parts (= C_0) to a sum of positive profit parts (= C_s), so that the recycling cost is constrained and minimized. In contrast, the recycling rate target ranges are changed as shown for the above 3 patterns. Additionally, a parameter β is set to weigh the average and the maximum of d_1^+ and d_2^-. In this study, a value of β is set as 0.5 to minimize the average and maximum deviation at the same time. All numerical experiments are performed by the same desktop PC, whose specification is Windows 7 with Inter(R) Core(TM) I 7-2600 CPU@3.40GHz.

4.3.2 Design example

Figure 4.2 shows the behaviors of the recycling cost for the recycling rate in the case of the cell phone. Additionally, fig. 4.3 shows the disassembly precedence relationships after environmentally friendly and economical parts selection at the pattern 1) all ranges in the case of the cell phone. A mark "X" in fig. 4.3 means the cancelled parts, which are not disassembled but removed by breaking without recycling rate and cost. In fig. 4.2, the marks "□", "○", "▵" signify the following:

□: Pattern 1) all ranges

○: Pattern 2) division into 3 areas

▵: Pattern 3) changing in increments of 10%

At the target range from 10% to 20%, from 20% to 30%, from 30% to 40%, from 40% to 50% and from 50% to 60% for the pattern 3) changing in increments of 10%, the same solution is found in these ranges. Additionally, at the target ranges from 60% to 70%, from 70% to 80% and from 80% to 90%, the same solution is found. Therefore, only 3 original solutions are found in the pattern 3) changing in increments of 10%, no matter where the 10 recycling rate target ranges are set in the changing in increments of 10%. To identify these causes, the selected parts at the recycling rate target range from 10% to 20%, and from 60% to 70%, which have the same solution as the other target ranges, are analyzed in detail in section 4.4.

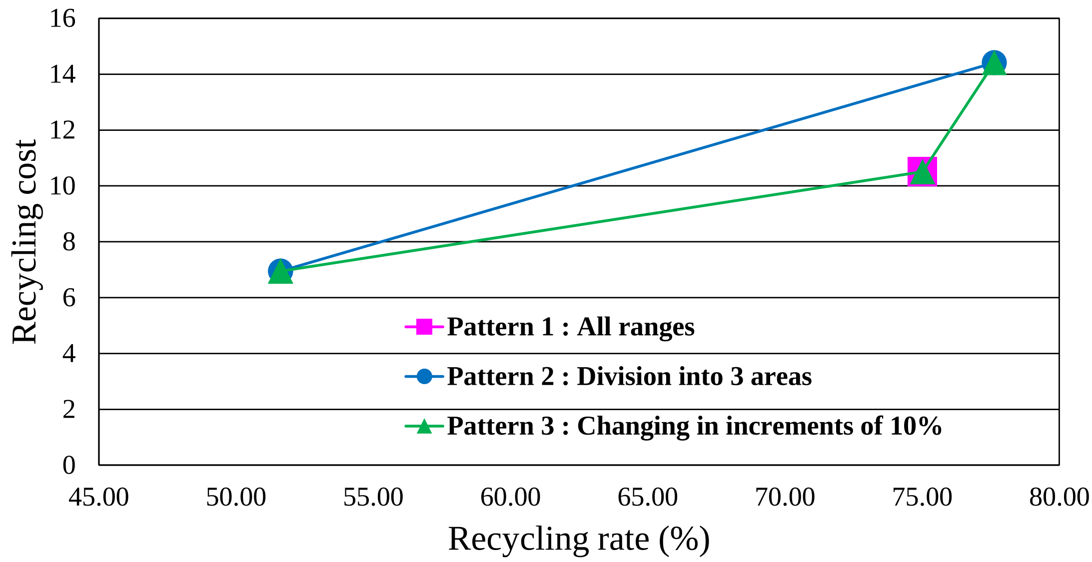

Figure 4.2 Behaviors of recycling cost for recycling rate by comparison: case of cell phone

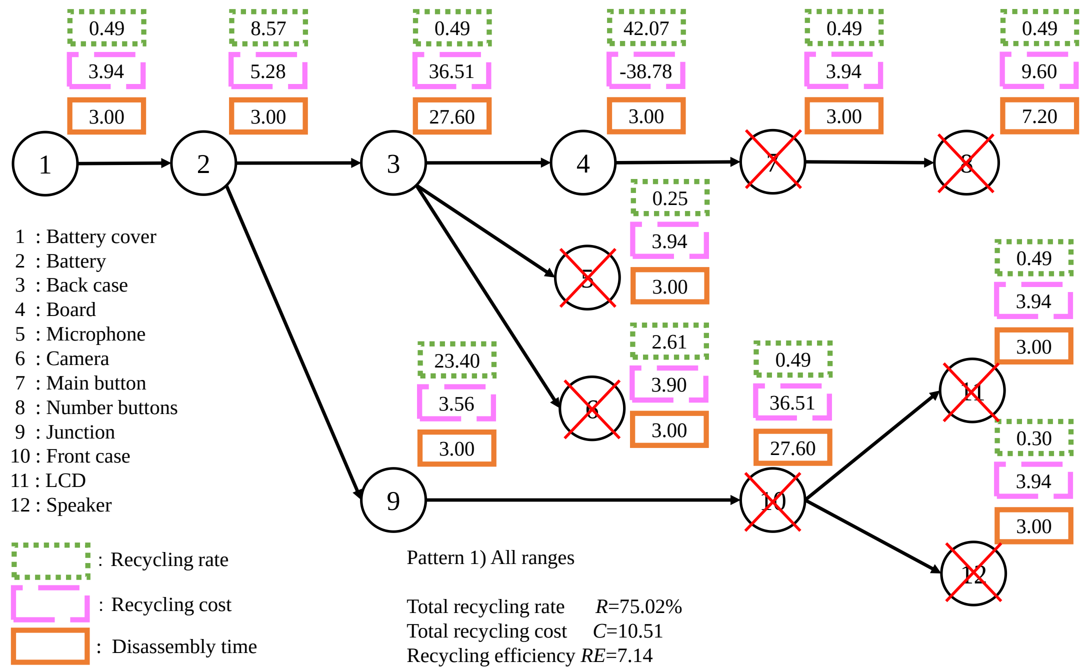

Figure 4.3 Disassembly precedence relationships after environmentally friendly and economical parts selection at Pattern 1) All ranges: case of cell phone

4.4 Experimental analysis

Section 4.4 discusses results of the proposed environmental friendly and economical disassembly parts selection by goal vector method by goal programming (GP) in terms of 2 research questions:

i) Are any common of different features among different assembled products resulted by the proposed environmentally friendly and economical parts selection?

ii) How to use the proposed GP effectively? i.e. How do we set the target ranges? / Are there any relationships between the number of target ranges and original solutions?

4.4.1. Comparison by product types: cell phone, computer vs. cleaner

(1) Harmonized solutions

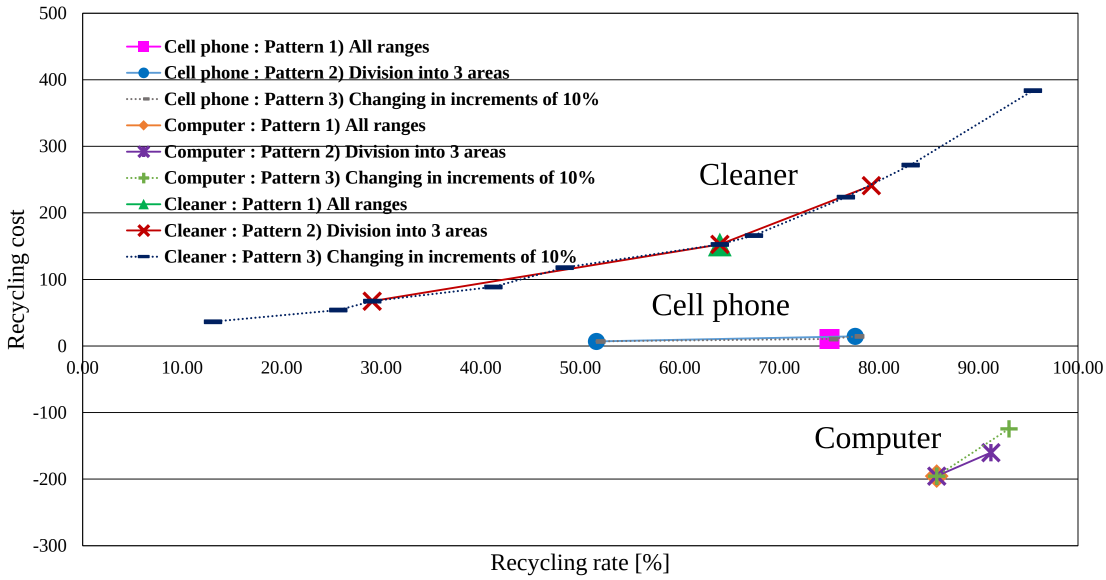

Figure 4.4 Behaviors of recycling rate for recycling cost in the case of cell phone, computer and cleaner

This subsection 4.4.1 adopts the environmentally friendly and economical disassembly parts selection to the computer and the cleaner in order to compare the different product types. Figure 4.4 shows behaviors of the recycling rate for the recycling cost in the cases of the cell phone, computer and cleaner. A solution that has a recycling rate over 50% and better recycling efficiency *RE* could be considered in this study as a harmonized solution for both the recycling rate and cost.

Throughout the 3 patterns, the harmonized solution is considered here, and is comprehensively based on not only recycling rate R and cost C but also on recycling efficiency RE. In the case of the cell phone, the solution found at the pattern 1) all ranges is selected as to harmonize the recycling rate and cost.

In the case of the computer, only 3 original solutions are found in the patterns 1) all ranges, 2) division into 3 areas and 3) changing in increments of 10%. One original solution, which is found in the pattern 1) all ranges, has the total recycling rate R=85.81%, cost C =-195.44, and efficiency RE=-0.44. Another solution, which is found in the pattern 2) division into 3 areas from 66% to 100%, has the total recycling rate R=91.26%, cost C=-160.13 and efficiency RE=-0.57. The other solution, which is found in the pattern 3) changing in increments of 10%, has the total recycling rate R=93.08%, cost C=-124.42 and efficiency RE=-0.75. These solutions satisfy the total recycling rate in regard to deciding the harmonized solution, because they have a recycling rate R over 80%. The maximum difference of the recycling rate is less than 8%, but one of the recycling cost is over 70. Thus, the minimum recycling cost solution found in the pattern 1) all ranges is more suitable for harmonizing the recycling rate and cost than the other 2 solutions.

In the case of the cleaner, the 11 original solutions are found in the patterns 1) all ranges, 2) division into 3 areas and 3) changing in increments of 10%. As in the case of computer, the total recycling rate R, cost C and recycling efficiency RE are taken into account. Therefore, it is said that the solution found in the pattern 1) all ranges is the recycling rate and cost coexistence solution.

(2) Effective and recommended patterns for searching solutions

By setting 3 patterns, the different target ranges and solutions can be obtained. This subsection discusses which patterns are effective or recommended, and how to use the 3 different patterns.

In the all cases of cell phone, computer and cleaner, the pattern 1) all ranges provided an effective solution to harmonize the recycling rate and cost in the experiments. With regard to pattern 2) division into 3 areas, it is said that this pattern could suggest multiple alternative solutions since it had a different total recycling rate R and cost C by comparing them to the pattern 1) all ranges.

However, the pattern 3) changing in increments of 10% has different features among the cases of the cell phone, computer and cleaner. In the case of the cell phone and computer, this pattern 3) changing in increments of 10% would not be necessary because the same or better solutions were found in the patterns 1) all ranges and 2) division into 3 areas. On the other hand, in the case of the cleaner, the 8 original solutions were found in the pattern 3) changing in increments of 10%. Thus, the pattern 3) changing in increments of 10% also should be effective in the case of the cleaner.

4.4.2 Effect of divisions for GP

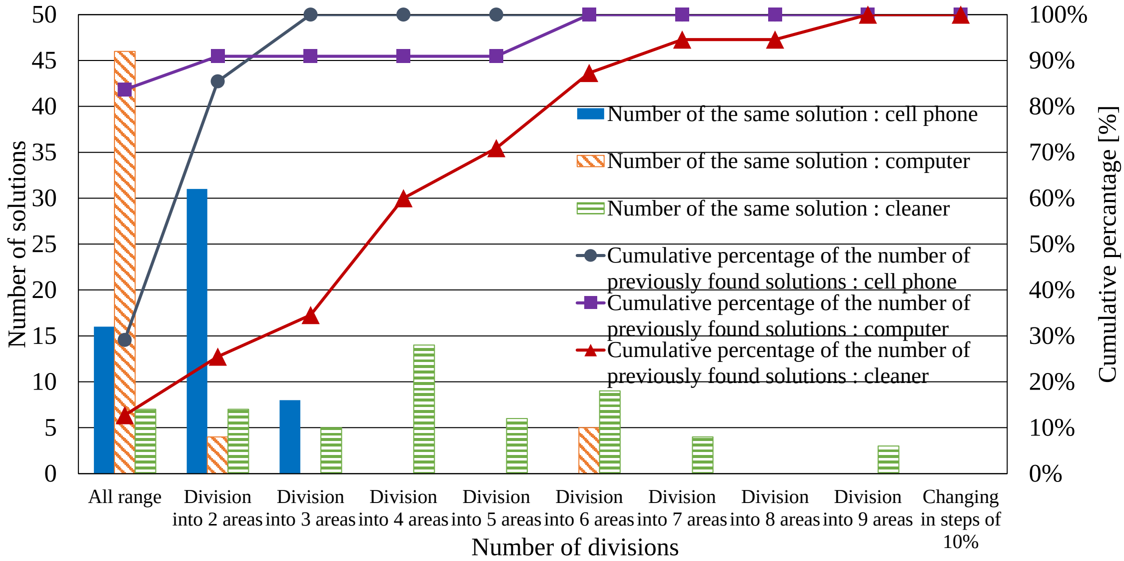

Figure 4.5 Number of same solutions and cumulative percentage of the number of previously found solutions: case of cell phone, computer and cleaner

In the proposed environmentally friendly and economical disassembly parts selection by GP, the difference between the tolerable and sufficient levels for each goal is a given and constant coefficient as shown in Eqs. (4.3) and (4.5). Thus, if the target ranges are changed, the results will be also changed. Therefore, this subsection examines the number of increased recycling rate divisions, and discusses the effect on the increment of the divisions.

(1) Relationships between original solutions and number of ranges

The original solution in this study is defined such that it is different from other solutions or not. For example, in the case of the cell phone at the patterns 2) division into 3 areas and 3) changing in increments of 10%, when there are the same solutions such as the recycling rate R=51.62% and cost C=6.95, the solution at the pattern 2) division into 3 areas from 0% to 33% means an original solution. Thus, the number of original solutions can be less than the number of setting target ranges.

The proposed environmentally friendly and economical disassembly parts selection is solved by changing the target ranges for the recycling rate by using cases of a cell phone, computer and cleaner. The number of divisions for the target ranges of the recycling rate are set and changed from one at all ranges to 10 areas by changing in increments of 10%. In contrast to the recycling rate, the target range of the recycling cost is also fixed as well as section 4.3. There are the 10 patterns set, which means 55 ranges, so that the 55 solutions are obtained, since 1 solution is obtained for each range.

Figure 4.5 shows the total number of the same solutions and the cumulative percentage of the number of previously found solutions for all solutions. In fig. 4.5, bars and marks signify the following:

- All bars show the number of the same solutions.
  Plain bar: cell phone
  Slash bar: computer
  Horizontal line bar: cleaner
- At all marks with lines show cumulative percentage of the number of previously found solutions.
  ○: cell phone
  □: computer
  ∆: cleaner

In the case of the cell phone, at all ranges, the number of the same solutions becomes 16, which equals the total number of the same solutions found in the other ranges. At division into 3 areas, all original solutions for all 55 ranges are found, so that the cumulative percentage of the number of previously found solutions for all solutions equals to 100%.

In all product cases, the same solutions are found at over 35 target ranges. In the case of the cell phone and the computer, only 3 original solutions are obtained in spite of 55 ranges set. Hence, the other 52 solutions are the same as the 3 original solutions. On the other hand, in the case of the cleaner, 19 original solutions are obtained, and the other 36 solutions are the same as the 19 originals. Therefore, in the case of the cell phone and computer, the new original solution except the solutions already obtained by the patterns 1) all ranges, 2) division into 3 areas and 3) changing in increment of 10% at section 4.3 is not found in the additional target ranges, though the target ranges increases. In contrast, in the case of the cleaner, the 8 new original solutions are obtained.

At the division into 3 areas, in the case of the cell phone and computer, the cumulative percentage of the number of previously found solutions for all solutions reaches over 90%. On the other hand, in the case of the cleaner, the cumulative percentage of the number of previously found solutions for all solutions is 35%, and one of the solutions found in division into 3 areas is the duplicate of the original solution found in all ranges.

At division into 4 areas, the 4 original solutions are obtained, and the cumulative percentage of the number of previously found solutions for all solutions is 25% higher than at division into 3 areas. This means that all solutions found in division into 4 areas are the originals, and 25% of all solutions are the same as the 4 originals. Therefore, it seems that division into 4 areas provides effective alternatives, such as covering the other ranges.

By focusing on Fig. 4.5, at division into 5, 6, 7, 8, 9 and 10 areas, it seems that the original solutions is less than the number of the target ranges set, and that the increase in the cumulative percentage slows down. Thus, it turned out that an increase over 3 divisions is not effective in the cases of the cell phone and computer, and that, the effective solutions may be obtained by 4 divisions in case of the cleaner.

(2) Effect of setting over 4 divisions among product features

By conducting the similar experiments to the cases of cell phone and computer, this subsection discusses relationships between the numbers of original solutions and of divisions. In the case of the cell phone and computer, only 3 original solutions are obtained, even though 55 ranges are set. Moreover, it turs out that the division into 3 areas is sufficient to obtain the best or alternative solutions.

In the case of the cleaner, the 19 original solutions and many of the same solutions as well as the case of the cell phone and computer are found at 55 ranges. The 9 original solutions are obtained from all ranges to division into 4 areas, and can replace the other 10 solutions.

Therefore, the different features are observed among the cases of the cell phone, computer and cleaner. It seems that the presence of negative cost (positive profit) parts and the total number of parts cause this difference. Most of the negative cost parts are made by metal so that the recycling rate becomes higher but recycling cost becomes lower. Thus, if the negative cost parts are selected for disassembly, the recycling rate R reaches several higher sufficient levels by maintaining the lower recycling cost. This causes the selected parts to remain unchanged, even though the target ranges changed. One of the reasons is that the cell phone and the computer have negative cost parts, while the cleaner has only positive cost parts.

If the total number of parts increased, the combinations of the select parts also changed. In the case of the cell phone and computer, the total number of parts is 12 and 14, respectively, while in the case of the cleaner, the total number of parts is 23. The cleaner, which consisted of only positive cost parts, promotes a variety of original solutions.

Therefore, if the total number of parts is less than 20 or if there are negative cost parts, division into 4 areas achieves the best and alternative solutions. Otherwise, it is enough to set division into 4 areas to obtain the best and alternative solutions.

4.5 Summary of bi-objective disassembly parts selectin for recycling rate and cost

This study proposed a bi-objective disassembly parts selection for recycling rate and cost by goal vector method by goal programming (GP) in terms of recycling rate and cost, discussed the differences of the results between the ε constraint method (Igarashi, Yamada and Inoue, 2014) and GP with the case of a cell phone, computer and cleaner, and examined the relationships between the number of the original solutions and target ranges. The main findings of the paper are as follows:

- The proposal method by GP in this study finds the same solutions with the lower number of numerical experiments as that with the ε constraint method (Igarashi, Yamada and Inoue, 2014).
- Pattern 1) all ranges is the best method for finding solutions, and harmonizes the recycling rate and cost.
- Pattern 2) division into 3 areas suggests multiple alternative solutions for the decision-makers to show the Pareto optimal ones.
- The desirable number of divisions would be 3 or 4 in the experiments.

5. Bi-objective disassembly parts selections for CO_2 saving rate and recycling cost

Chapter 4 presented the bi-objective disassembly parts selection for recycling rate and cost, and examined the relationships between the number of original solutions and target ranges. The maximizing the recycling rate will reduce disposal weight, so that consumption of natural resources will be also reduced by promoting recycling. Regarding to environmental indices, CO_2 saving rate also contributes to different but related global environmental issues such as material starvation and global warming. The CO_2 saving rate can define as a rate of the CO_2 volumes in part of assembly products production for each disassembled and collected part which saves the virgin parts/materials to the total CO_2 volumes of the whole product (Igarashi et al., 2014). Therefore, this chapter focuses on the CO_2 saving rate instead of the recycling rate, and proposes another bi-objective disassembly parts selection for CO_2 saving rate and cost.

5.1 Overview of another bi-objective disassembly parts selections for CO_2 saving rate and recycling cost

The environmental indices such as the recycling and CO_2 saving rates depend on material types and weights. However, each material has different trends for them. For example, since cloth/fiber is difficult for recycling, the recycling rate tends to be lower than that of steel. In contrast, the CO_2 emissions for cloth/fiber production is generally higher than that of metals. Then, the CO_2 saving rate of the cloth/fiber tends to be higher than that of medals. Therefore, by using the different environmental indices, namely CO_2 saving and recycling rates, the collected material types and weights will be different. In order to pursue cost effectiveness of recycled weights by each material, one of the design issues about disassembly parts is come up with as follows: (1) Which types of materials are recycled by increasing the recycling or the CO_2 saving rates? How much weights is recycled for each material? How much cost is required for recycling?, (2) Are there the same or different cost effectiveness for recycled weights by types of materials between the recycling and the CO_2 saving rates?

This chapter proposes another bi-objective disassembly parts selection, and compares the results between bi-objective disassembly parts selections for recycling rate and cost and for CO_2 saving rate and cost. Additionally, collected materials are analyzed to examine differences of collected material weight between 2 different types of bi-objectives.

5.2 Formulation of another bi-objective disassembly parts selection by goal programming

This section formulates another bi-objective for minimizing recycling cost, while maximizing CO_2 saving rate.

The new notations are presented as below:

e_j	:	CO_2 saving rate at part *j*
E_{max}	:	CO_2 saving rate when all parts are disassembled
E_0	:	Tolerable total CO_2 saving rate
E_s	:	Sufficient total CO_2 saving rate
E	:	Total CO_2 saving rate

By transposing r_j, and R in Eq. (4.2) in chapter 4 to e_j and E, respectively, another bi-objective functions are obtained as shown in Eqs. (5.1) and (5.2) as follows:

$$C = \sum_{j=1}^{N} c_j x_j \rightarrow Min \tag{5.1}$$

$$E = \sum_{j=1}^{N} e_j x_j \rightarrow Max \tag{5.2}$$

Similar to the bi-objective for recycling rate and cost in chapter 4, another bi-objective disassembly parts selection is formulated using goal vector method by goal programming (GP). Then, the Eqs. (4.5) and (4.6) in chapter 4 are switched to Eqs. (5.3) and (5.4) by using the above new parameters as below:

Goal: minimize d_2^-

Subject to:

$$E + (E_0 - E_s)(d_2^- - d_2^+) = E_s \tag{5.3}$$

$$E \leq E_0 \tag{5.4}$$

By setting the proper target ranges for total CO_2 saving rate, another bi-objective disassembly parts selection can also obtain Pareto optimal solutions.

5.3 Design example of another bi-objective disassembly parts selection

(1) Problem example

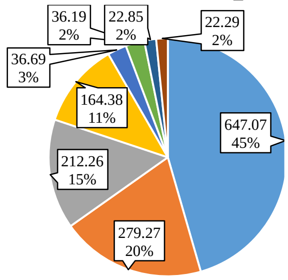

Figure 5.1a Input data of material weights in the case of a vacuum cleaner

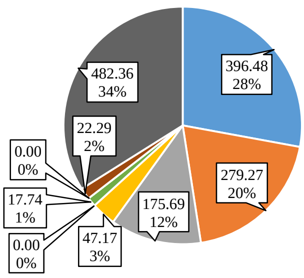

Figure 5.1b Results of recycled weights in a case of recycling rate and cost at all ranges

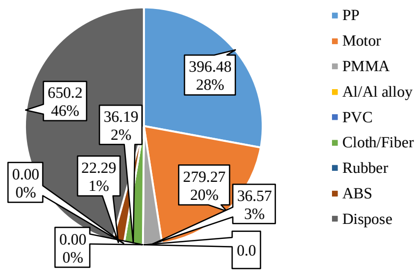

Figure 5.1c Results of recycled weights in a case of CO_2 saving rate and cost at all range

This section adopts a vacuum cleaner as an example of a product to test the environmentally friendly and economical disassembly parts selection for the CO_2 saving rate and the recycling cost by GP. The vacuum cleaner has 23 original parts without any missing part, with the assumption that the conditions for all parts are good and available. The total recycling cost and the CO_2 saving rate with all parts disassembled are 402.17 and 100% (=E_{max}), respectively. Figure 5.1a shows each material weight and percentage against for the whole product weight in the case of the vacuum cleaner, with the total product weights being 1,421[g] and 8 types of materials, namely Polypropylene (PP), polyvinyl chloride (PVC), Poly methyl methacrylate (PMMA), Cloth/Fiber, Al/Al alloy, Acrylonitrile butadiene styrene (ABS), Motor, and Rubber. It is shown that PP which the 11 out of 23 parts of the vacuum cleaner are made of is the heaviest material at 647.07 [g]. Figure 5.2 shows the disassembly precedence relationships with the recycling cost, material type and weights in the case of the vacuum cleaner. Each element shows each part connected with plain-line or dotted-line arrows each other. The plain-line arrows means disassembly preceding relationships, while dotted-line arrows means no constraint relationships among parts (Igarashi, Yamada and Inoue, 2014). The disassembly precedence relationships provide a visual representation of ordering disassembly tasks/parts based on immediate predecessors (McGovern and Gupta, 2011). The selection of environmentally friendly and economical disassembly parts is carried out using the relationships in Fig. 5.2.

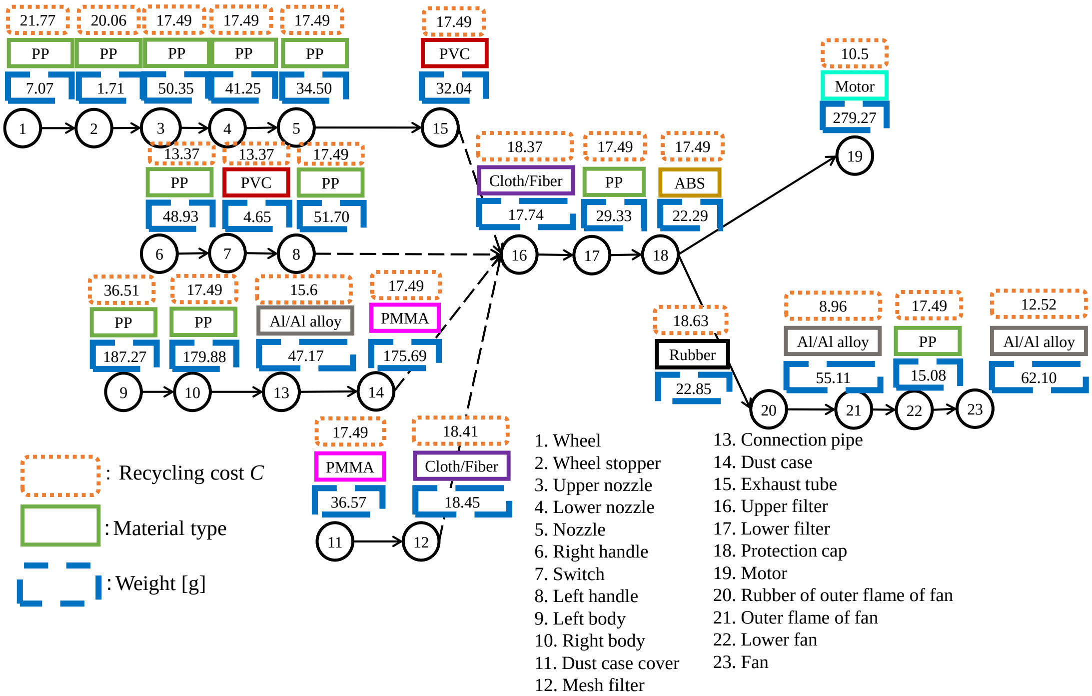

Figure 5.2 Disassembly precedence relationships with recycling cost, material type and weight: case of cleaner

(2) Goal programming adaptation

Similar to bi-objective for recycling rate and cost in chapter 4, this study adopts GP to the proposed bi-objective disassembly parts selection for CO_2 saving rate and recycling cost. It requires setting of the sufficient and tolerable levels for each goal. To compare the results with the recycling rate and cost in chapter 4, the CO_2 saving rate target ranges are changed to 4 patterns as well as in chapter 4, in order to obtain Pareto optimal solutions harmonizing the total recycling cost C and the total CO_2 saving rate E. According to analysis of changing target ranges in chapter 4, the division into 4 areas are enough to obtain the best and alternative solutions. Therefore, this study also set patterns 1) all ranges, 2) division into 2 areas, 3) division into 3 areas and 4) division into 4 areas as combinations of target rages of CO_2 saving rate. The patterns are set to divide the feasible CO_2 saving rate range equally, which are defined from 0% (no disassembly parts) to 100% (=E_{max}: all parts disassembled). The details of the patterns of CO_2 saving rate target ranges are as follows:

Pattern 1) All ranges from 0% to 100% (E_0=0%, E_s=E_{max}),

Pattern 2) Division into 2 areas from 0% to 50% (E_0=0%, E_s=E_{max}×50%) and from 50% to 100% (E_0=50%, E_s=E_{max}),

Pattern 3) Division into 3 areas from 0% to 33% (E_0=0%, E_s=E_{max}×33%), from 33% to 66% (E_0=E_{max}×33%, E_s=E_{max}×66%) and from 66% to 100% (E_0=E_{max}×66%, E_s= E_{max})

Pattern 4) Division into 4 areas from 0% to 25% (E_0=0%, E_s=E_{max}×25%), from 25% to 50% (E_0=E_{max}×25%, E_s=E_{max}×50%), from 50% to 75% (E_0=E_{max}×50%, E_s= E_{max}×75%) and from 75% to 100% (E_0=E_{max}×75%, E_s= E_{max})

In contrast to the CO_2 saving rate target ranges, the steady target range of the recycling cost is set from a sum of negative cost parts (=C_0) to a sum of positive profit parts (=C_s), so that the recycling cost is minimized. Then the environmentally friendly and economical disassembly parts selection is carried out with the above recycling cost and CO_2 saving rate target ranges under the disassembly precedence relationships as shown in Fig. 5.2. By using the mathematical programming package developed by Numerical Optimizer (NTT DATA Mathematical System Inc.), all numerical experiments are performed by the same desktop PC with the following specifications: Windows 7 with Intel(R) Core(TM) I7-2600 CPU@3.40GHz.

(3) Design example

This subsection explains the solutions obtained from the experiments. Table 5.1 shows the input data such as the recycling cost and the CO_2 saving rate for each part, and the results of the disassembly parts selection. The circles "○" in Table 5.1 denote the selected parts for recycling, while the non-marked indicates the destroyed parts without the recycling cost. 10 solutions are obtained from the numerical experiments since 10 target ranges of the CO_2 saving rate are set in 4 patterns. The 3 solutions in patterns 3) from 0% to 33% and from 33% to 66%, 4) from 50% to 75% are duplicated with ones of other solutions as shown in Table 5.1. It is assumed that the part #19 motor is always disassembled and removed from the percentage of CO_2 saving rate as well as Igarashi et al. (2014) since it has too high CO_2 volumes (95% of the whole volumes). To disassemble #19 motor in the parts selection, the 3 parts including #16 upper filter, #17 lower filter and #18 protection are selected in all solutions because the 3 parts are preceded to #19 motor as shown in Fig. 5.2.

From table 5.1, it observes that a solution at pattern 1) all ranges selects 54% of the whole weight for recycling, and has the total CO_2 saving rate E=59.80% and total recycling cost C=153.75, respectively. In addition, PP is recycled by 396.48 [g], while all parts made of Al/Al alloy are not selected.

In another case of pattern 4) division into 4 areas from 25% to 50%, the selected parts have 79% of the whole product weight, and bring the total CO_2 saving rate E=50.21% and recycling cost C=127.34, respectively. With respect to the total CO_2 saving rate, the differences between them is only 9.59%. The recycled weights of PP and Al/Al alloy are different by 367.15 [g] and 55.1 [g], respectively. In a rate of recycled weight against contained weight, the differences of them becomes 56.74% and 33.63%, respectively. Thus, it is found that obtained types of materials, recycled weights for each material and cost are different by each target range given.

Table. 5.1 Bill of materials with disassembly parts selection for recycling cost and CO_2 saving rate: case of a vacuum cleaner

No.	Part name	Material type	Disassembly operation	Weight [g]	CO_2 saving rate [%] e_j	Recycling rate [%] r_j	Recycling cost c_j	Patterns						
								Pattern 1) all ranges	Pattern 2) Division into 2 areas		Pattern 3) Dicision into 3 areas	Pattern 4) Dicision into 4 areas		
								Target ranges of the CO_2 saving rate [%]						
								0~100% 33%～66%	0~50% 50~75%	50~100% 0%～33%	66~100%	0~25%	25~50%	75~100%
1	Wheel	PP	[move right]	7.07	0.62	0.99	21.77							
2	Wheel stopper	PP	[move up]	1.71	0.15	0.24	20.06							
3	Upper nozzle	PP	[move up]	50.35	2.22	3.52	17.49							
4	Lower nozzle	PP	[move up]	41.25	1.82	2.89	17.49							
5	Nozzle	PP	[move up]	34.50	1.52	2.41	17.49							
6	Right handle	PP	[screw][move up]	48.93	2.18	3.42	13.37							○
7	Switch	PVC	[screw][move up]	4.65	0.60	0.32	13.37							
8	Left handle	PP	[move up]	51.70	2.28	3.62	17.49							
9	Left body	PP	[screw 4][move up]	187.27	8.30	13.10	36.51	○		○	○			○
10	Right body	PP	[move up]	179.88	7.92	12.58	17.49	○		○	○			○
11	Dust case cover	PMMA	[move up]	36.57	3.08	2.56	17.49	○	○	○	○		○	○
12	Mesh filter	Cloth/Fiber	[move up]	18.45	19.28	0.00	18.41	○	○	○	○		○	○
13	Connection pipe	Al/Al alloy	[screw 2][move up]	47.17	2.16	3.30	17.31			○	○			○
14	Dust case	PMMA	[move up]	175.69	15.21	12.29	17.49			○	○			○
15	Exhaust tube	PVC	[move up]	32.04	1.27	2.24	17.49							
16	Upper filter	Cloth/Fiber	[move up]	17.74	18.53	0.00	18.37	○	○	○	○	○	○	○
17	Lower filter	PP	[move up]	29.33	1.29	2.05	17.49	○	○	○	○	○	○	○
18	Protection cap	ABS	[move up]	22.29	1.39	1.56	17.49	○	○	○	○	○	○	○
19	Motor	Motor	[move up]	279.27	0.00	19.14	10.50	○	○	○	○	○	○	○
20	Rubber of outer frame of fan	Rubber	[move up]	22.85	4.00	0.00	18.63				○	○	○	○
21	Outer frame of fan	Al/Al alloy	[screw][move up]	55.11	2.64	3.85	8.96				○		○	○
22	Lower fan	PP	[move up]	15.08	0.66	1.06	17.49							
23	Fan	Al/Al alloy	[move up]	62.10	2.85	4.34	12.52							
Total				1421.00	100.00	95.48	402.17							
Average				61.78	4.35	4.15	17.49							
Standard deviation				70.19	5.58	4.97	4.98							

5.4 Comparison of bi-objectives for CO_2 saving rate vs. recycling cost and recycling rate vs. cost

This section compares the results of 2 different bi-objectives for recycling rate and cost in chapter 4 and for CO_2 saving rate and recycling cost in order to find whether there are any similar or different cost effectiveness for recycled materials between CO_2 saving and recycling rates. As shown in table 5.1, each part has different CO_2 saving and recycling rates and cost. By adding recycling rate r_j of selected parts, the total recycling rate R is also obtained in this study for CO_2 saving rate and recycling cost. For example, the total recycling rate R at pattern 1) all ranges in this study becomes 50.99% by adding the recycling rate r_j of the selected 8 parts as shown in table 5.1. As using the similar way, the total CO_2 saving rate E in chapter 4 is also calculated.

The total CO_2 saving and recycling rates for the total recycling cost in chapter 4 are shown in Figs. 5.3a and 5.3b, respectively. The marks "□" and "△" in Figs. 5.3a and 5.3b indicate the plots for recycling rate and cost in chapter 4, and for CO_2 saving rate and cost in this chapter. The both of vertical axises mean the total recycling cost C, while the horizontal axises mean the total CO_2 saving and recycling rates, respectively. All solutions in Fig 5.3a are the same as ones in Fig. 5.3b. However, all plotted locations are different between Figs. 5.3a and 5.3b since the horizontal axises are different.

From Figs. 5.3a and 5.3b, it can be observed that the recycling cost generally increases as the recycling and CO_2 saving rates increase in both cases. Also, it turns out the green line with triangle marks is generally located under the blue line with square marks in Fig. 5.3a since the bi-objective in this study has priority to select the parts with higher CO_2 saving rate but lower recycling cost. For example, the part #12 mesh filter with higher CO_2 saving rate by 19.28% but recycling rate by 0% has more priority than ones of the parts #9 left and #10 right bodies and is selected in all solutions except the solution with the lowest total CO_2 saving rate.

On the other hand, the blue line with square marks is generally located under the green line with triangle marks in Fig. 5.3b due to the similar reasons. Hence, the #9 left and #10 right bodies are selected for all solutions in chapter 4. The sum of the recycling rate of these parts are 25.68% with recycling cost by 54.00.

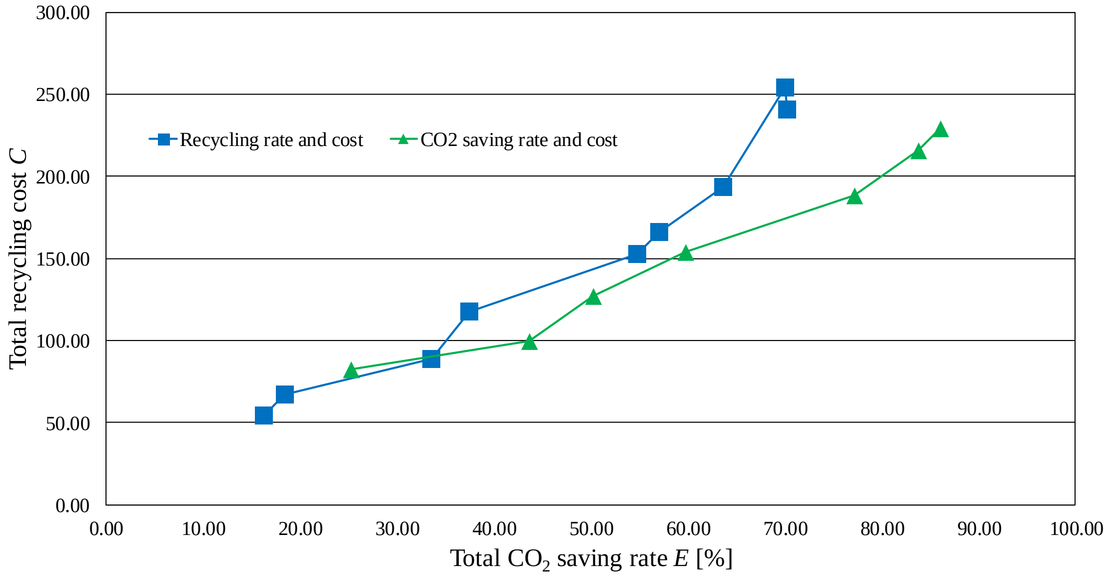

Figure 5.3a Behaviors of recycling cost for CO_2 saving rate: case of bi-objective optimization by goal programing

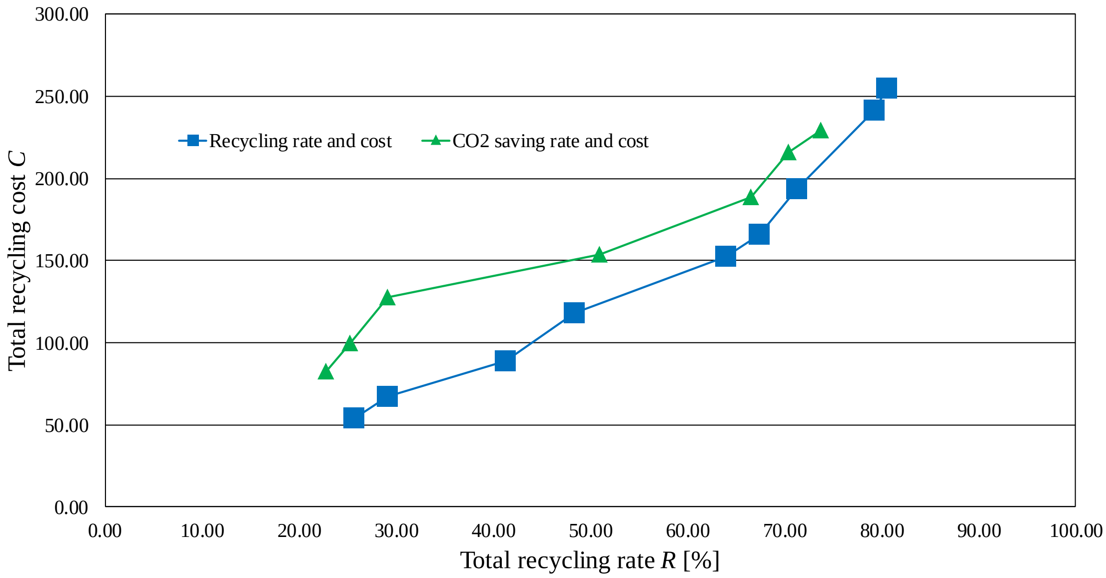

Figure 5.3b Behaviors of recycling cost for recycling rate: case of bi-objective optimization by goal programing

Even though the general behaviors in both cases in Figs. 5.3a and 5.3b become similar, there are not the same plots in both Figs. 5.3a and 5.3b. One of the reasons is that the combinations of the selected parts for CO_2 saving rate and recycling cost are not duplicated with ones for recycling rate and cost in chapter 4. Figures 5.1b and 5.1c show that results of recycled materials in bi-objectives for recycling rate and cost and for CO_2 saving rate and cost at pattern 1) all ranges, respectively. By comparing the selected materials at the pattern 1) all ranges in the bi-objectives for recycling rate and cost and for CO_2 saving rate and cost as shown in Figs. 5.1b and 5.1c, it turns out that the selected material and weight are different. For example, parts made of Al are selected by 47.17 [g] for recycling in the bi-objective for recycling rate and cost in chapter 4, while these parts made of Al are not selected in this study.

By setting the different environmental objective functions such as maximizing CO_2 saving and recycling rates, the different recycled materials are obtained, even though the similar trends such as increasing the total recycling cost as the CO_2 saving or recycling rates increase are observed.

Additionally, a square shaped plot with the highest CO_2 saving rate is located under than one with the 2nd highest CO_2 saving rate as shown in Fig. 5.3a. This is caused that the differences between CO_2 saving and recycling rates of #11 dust case cover made of PMMA. As shown in table 5.1, the CO_2 saving rate about 17 out of 23 parts is lower than the recycling rate for each part. The solution with highest total CO_2 saving rate contains #11 dust case cover, while one with the 2nd highest CO_2 saving rate contains #7 switch and #8 left handle instead of #11 dust case cover. It finds out from table 5.1 that the CO_2 saving rate of #11 dust case cover is higher than the sum of the CO_2 saving rate of #7 switch and #8 left handle, while the recycling cost of #11 dust case cover is lower than the sum of the recycling cost of them. Therefore, the differences between CO_2 saving and recycling rates can increase total CO_2 saving rate in the bi-objective optimization for recycling rate and cost despite decreasing the recycling cost.

By focusing on the differences between the CO_2 saving and recycling rates for each part as shown in table 5.1, the parts made of cloth/fiber and rubber have the higher CO_2 saving rate than the recycling rate. The rubber and cloth/fiber are difficult for material recycling, and the recycling rate of the parts made of them become 0%. By setting CO_2 saving rate as an objective function, it is found that these parts made of rubber and cloth/fiber seem to be prioritized for recycling.

5.5 Summary of bi-objective disassembly parts selection for CO_2 saving rate and recycling cost

This section proposed another bi-objective disassembly parts selection for CO_2 saving rate and cost, compared the behaviors of the CO_2 saving/recycling rate for recycling cost, and analyzed the collected material types in each bi-objective disassembly parts selection. Through the numerical experiments, there are 3 findings were observed as follows:

- The behaviors of the CO_2 saving/recycling rate for recycling cost were almost same. Both of the total recycling cost increased as the CO_2 saving or recycling rate increased.
- There was not any same combinations of the selected parts between the results of 2 types of bi-objective disassembly parts selections. Thus, the squares and triangles in Figs. 5.3a and 5.3b were not duplicated.
- A case was found that the breakdown of collected materials was different, even though the values of total CO_2 saving/recycling rate and total recycling cost was almost same. The bi-objective for recycling rate and cost would collect more metals al/al alloy than that of another bi-objective for CO_2 saving rate and cost. On the other hand, the bi-objective for CO_2 saving rate and cost tends to retrieve more cloth/fiber and rubber, which have higher carbon dioxide emission intensity.

6 Disassembly-to-order system with uncertainties of EOL product

Chapter 6 presents a disassembly production planning for profit and disposal weight in the disassembly-to-order (DTO) system using liner physical programming (LPP). In section 6.1, the recovery processes and costs for component reuse and material recycling in the DTO system is described. Section 6.2 formulates the disassembly production planning using LPP. To illustrate a design example, a desktop PC is used in section 6.3. Section 6.4 summarizes the proposed disassembly production planning using LPP.

6.1 Overview of disassembly-to-order system with uncertainties of EOL product

This section explains the procedures and processes from the purchased EOL products to satisfy the reusable component and recyclable material demands in the DTO system. Procedure from collecting EOL products to satisfying the reuse components and recycle materials demands in the DTO system is explained based on Kinoshita, Yamada and Gupta (2019b).

6.1.1. Procedures of purchasing EOL products to fulfill the reuse and recycle demands in the DTO system

Figure 6.1 shows procedure of a DTO system for reuse components and recycled materials. Green circles in Fig. 6.1 indicate each element in the DTO system, while red and blue rhombus mean decision making processes. The decision makings in red rhombus depend on each component condition including uncertainties. On the other hand, the decision makings in blue rhombus depend on production/storage capacities, and demand. The proposed DTO system determines the optimal combinations of the EOL products and the components for each process and route to satisfy the static demands of reuse components and recycled materials. The EOL products with different statuses are provided from multiple suppliers. These different statues lead to different disassembly stochastic yields. The purchased EOL products are collected to determine whether non-destructive disassembly for reuse or destructive disassembly for recycle.

The components disassembled with non-destructive operation without damage are sent to an inspection for reuse. Only components with good condition can be pass the inspection and satisfy the demand of reuse components. The proposed model does not allow supply shortage. Then, outside components procurement is available if the supply of components removed from the purchased the EOL products is less than the reuse demand. In a case that the supply of reuse components reaches the demand, the excess of the reuse components are sent to the storage. There is an inventory capacity for reuse components. Then, the excess of reuses components are disposed if the storage filled up.

With regarding to material recycling, the components with destructive disassembly and with bad condition for reuse are sent to a recycling inspection. The components without hazardous materials can pass the recycling inspection as a good recyclable components, while the components with hazardous materials are disposed with hazardous disposal cost. The recyclable components are sorted into each material type with recycling rate. The in-plant facilities are used until the volumes of recycling weight reaches the in-plant recycling capacity. If a processing capacity at the in-plant facility is filled, the recyclable components are sent to an out-plant facility. Similar to reuse processes, the outside procurement components and recycled material storage are available.

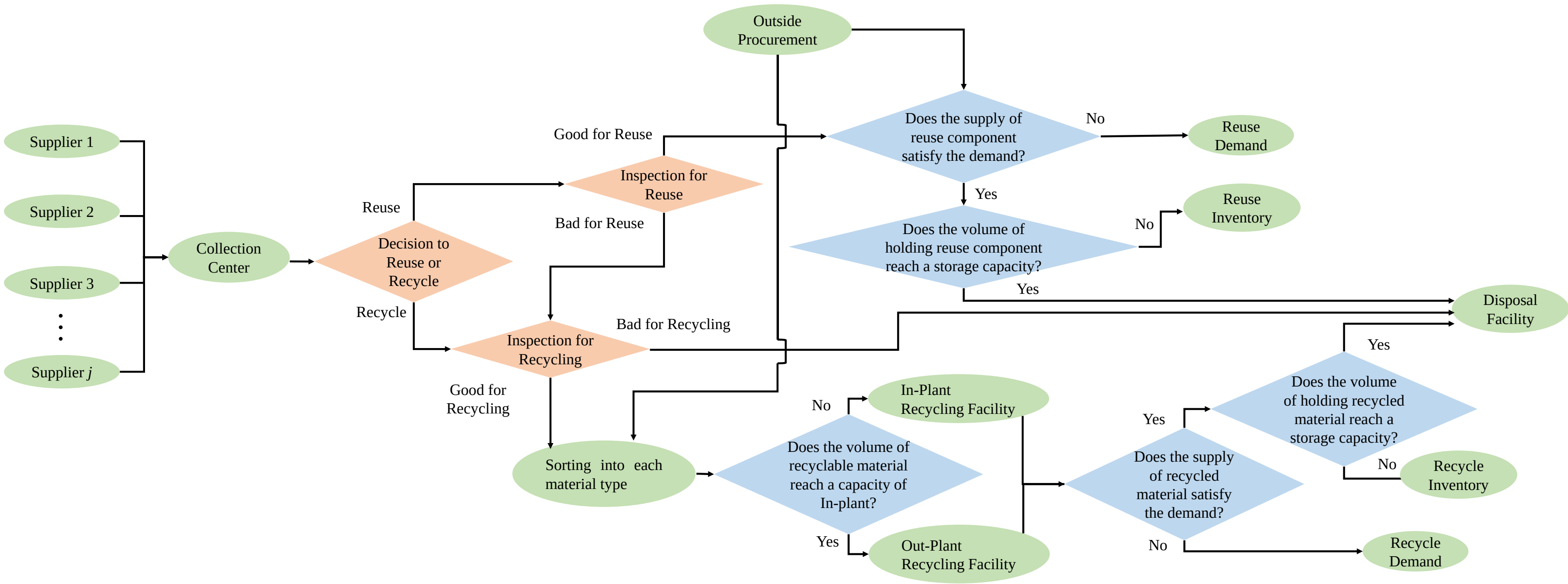

Figure 6.1 Disassembly-to-order system for decision to reuse or recycle

6.1.2. Revenue and cost in DTO system

The proposed DTO system was constructed based on the system developed by Massoud and Gupta (2010). To satisfy both the reuse and recycling demands, the DTO system determines several quantities, such as the numbers of purchased EOL products, components procured from outside suppliers, and reusable components and recyclable materials. Therefore, 2 types of revenues and 6 types of costs are addressed in the DTO system:

Revenue of reusable components

The revenue of reusable components is calculated by multiplying the number of sold reusable components by the reusable selling price for each component. The reusable demand is given as input data.

Revenue of recyclable materials

Similar to the revenue of reusable components, that of recyclable materials is calculated by multiplying the volume of sold recyclable materials by the recyclable selling price for each material. It is assumed that each component is made of one material. The recyclable material demand is also given as input data.

Purchased cost of EOL products from suppliers

Each supplier provides EOL products of different qualities at different costs. Hence, different EOL products purchased from different suppliers are assumed to have different stochastic disassembly yields.

Disassembly cost

The disassembly cost can be divided into 2 types: nondestructive and destructive. The non-destructive disassembly cost is the cost required to retrieve the reusable components from the EOL products carefully without damage. In contrast, the destructive disassembly cost is accrued when retrieving the recyclable components by crushing. Therefore, the nondestructive disassembly costs become more expensive than the destructive disassembly costs, owing to the labor cost (Joshi and Gupta, 2017; Yamada, 2008).

Procured cost of additional components

The procured cost is paid to outside component suppliers when the reusable and recyclable components are procured from them to fulfill the reusable component and recyclable material demands.

Inventory cost

The inventory cost consists of reusable components and recyclable materials holding costs. The reusable components holding cost is more expensive than the recyclable materials holding cost, as reusable components need to be kept in good storage conditions to preserve their functions.

Recycling cost

Recycling processes are required to regain the added material value from the retrieved components. It is assumed that the recycling cost at an in-plant recycling facility is cheaper than that at an out-plant recycling facility.

Disposal cost

Disposal cost is defined as the sum of two different types of processes. One cost is for the disposal of excess reused components and recycled materials, while the other is for the proper disposal of hazardous components.

The proposed DTO system attempts to achieve higher profit, lower disposal weight, lower purchased cost, and lower procured cost under stochastic disassembly yields. Profit is defined as the differences between the sum of revenues and that of costs (Massoud and Gupta, 2010).

6.2 Mathematical model

Notations and formulation of a DTO system by using LPP is presented in this section. Subsection 6.2.1 lists the parameters and variables used in this study and formulates the DTO objectives. Subsection 6.2.2 sets the constraints of the DTO system. Subsection 6.2. 3 adapts LPP to solve the multi-objective DTO problem and transposes the objectives to constraints with positive/negative limits and deviation variables to introduce an aggregate objective function.

6.2.1 Notation and objective functions of DTO system

The parameters and variables used in this paper are listed below:

(i) Sets

I	:	Set of EOL products
J	:	Set of suppliers for EOL products
K	:	Set of components
M	:	Set of materials

(ii) Indices

i	:	Index of EOL products
j	:	Index of suppliers for EOL products
k	:	Index of components/materials
m	:	Index of materials
p	:	Index of objective functions (p=1,2,3,4)
s	:	Index of disability ranges in LPP (s=2,3,4,5)

(iii) Variables

TP	:	Total profit

TDW	:	Total disposal weight
TPURC	:	Total purchased cost of EOL product
TPRC	:	Total outside procurement cost of additional components
RUR	:	Total revenue of reusable components
RCR	:	Total revenue of recyclable materials
TDAC	:	Total disassembly cost
TINVC	:	Total inventory cost
TRCC	:	Total recycling cost
TDPC	:	Total disposal cost
Q_{ij}^{EOL}	:	Quantity of purchased EOL product *i* from supplier *j*
Q_k^{PR}	:	Quantity of outside procurement component *k*
Q_k^{RUPR}	:	Quantity of outside procurement for reused component *k*
Q_k^{RCPR}	:	Quantity of outside procurement for recycled material *m* contained in component *k*
Q_k^{DA}	:	Quantity of disassembly component *k*
Q_k^{NDA}	:	Quantity of non-destructive component *k*
Q_k^{DDA}	:	Quantity of destructive component *k*
Q_k^{GNDA}	:	Quantity of reusable component *k* with non-destructive disassembly
Q_k^{BNDA}	:	Quantity of non-reusable component *k* with non-destructive disassembly
Q_k^{GDDA}	:	Quantity of recyclable component *k*
Q_k^{BDDA}	:	Quantity of non-recyclable component *k* with hazardous materials
Q_k^{RU}	:	Quantity of reused component *k*
Q_m^{RC}	:	Weight of recycled material *m*
Q_m^{RCW}	:	Recyclable weight of recycled material *m*

Q_m^{IRC}	:	Weight of recycled material *m* at in-plant recycling facility
Q_m^{ORC}	:	Weight of recycled material *m* at out-plant recycling facility
$Excess_k^{RU}$	:	Excess quantity of reused component *k*
$Excess_m^{RC}$	:	Excess weight of recycled material *m*
Q_k^{EInvRU}	:	Final inventory quantity of reused component *k*
Q_m^{EInvRC}	:	Final inventory weight of recycled material *m*
Q_k^{RUDP}	:	Disposal quantity of reused component *k*
Q_m^{RCDP}	:	Disposal weight of recycled material *m*
d_{ps}^{+}, d_{ps}^{-}	:	Positive/Negative deviation variable from *s*th range of objective *p*

(iv) Parameters

D_k^{RU}	:	Demand for reused component *k*
D_m^{RC}	:	Demand for recycled material *m*
sru_k	:	Resale value of reused component *k*
src_m	:	Resale value of recycled component *m*
prc_k	:	Outside procurement cost of component *k*
p_{ij}	:	Purchase cost of EOL product *i* from supplier *j*
dpc_k^{RU}	:	Disposal cost of reused component *k*
dpc_m^{RC}		Disposal cost of recycled material *m*
$hdpc_k$	:	Hazardous disposal cost of component *k*
$ndac_k$	:	Nondestructive disassembly cost of component *k*
$ddac_k$	:	Destructive disassembly cost of component *k*
$ruhc_k$	:	Holding cost of reused component *k*
$rchc_m$	:	Holding cost of recycled material *m*
$ircc_m$	:	In-plant recycling cost of material *m*

$orcc_m$	:	Out-plant recycling cost of material *m*
w_k	:	Weight of component *k*
r_k	:	Rate of recyclable weight of component *k*
Num_{ijk}	:	Number of components *k* in EOL product *i* from supplier *j*
yld_{ijk}	:	Disassembly yields of component *k* in EOL product *i* from supplier *j*
PCT_k^{RU}	:	Reuse percentage of component *k*
PCT_k^{RC}	:	Recycling percentage of component *k*
Cap_k^{InvRU}	:	Inventory capacity of reused component *k*
Cap_m^{InvRC}	:	Inventory capacity of recycled material *m*
Cap_m^{IRC}	:	In-plant recycling capacity of material *k*
Cap_{ij}^{EOL}	:	Supply capacity of EOL product *i* from supplier *j*
Q_k^{SInvRU}	:	Initial inventory quantity of reused component *k*
Q_m^{SInvRC}	:	Initial inventory weight of recycled material *m*
t_{ps}^{+}, t_{ps}^{-}		Positive/Negative limit to the *s*th range of objective *p*
$\widetilde{w}_{ps}^{+}, \widetilde{w}_{ps}^{-}$		Positive/Negative deviation weight of the *s*th range of objective *p*

To solve the DTO problem, this study sets 4 objective functions. The first objective is to maximize the total profit, defined as differences between 2 resale revenues and 6 costs in the DTO system. The total profit comprises total revenue of reusable components (*RUR*), total revenue of recyclable materials (*RCR*), total EOL purchased cost (*TPURC*), total procurement cost of additional components (*TPRC*), total disposal cost (*TDPC*), total disassembly cost (*TDAC*), total inventory cost (*TINVC*), and total recycling cost (*TRCC*). Then, the total profit *TP* is formulated as

$$\begin{aligned} TP = RUR + RCR - TPURC - TPRC \\ -TDPC - TDAC - TINVC - TRCC \end{aligned} \tag{6.1}$$

The 2nd objective is to minimize the total disposal weight. To save additional consumption of natural resources with material circulation, the DTO system should minimize the disposal weight. 1st element $(Q_k^{DA} + Q_k^{PR})w_k$ indicates the total input volumes of the DTO system from the EOL suppliers and the outside components provider. The 2nd element $(D_k^{RU} + Q_k^{EInvRU})w_k$ means the total weight of reused components. The last element $(D_m^{RC} + Q_m^{EInvRC})$ represents the total weight of recycled materials. Then, the total disposal weight can be formulated as

$$TDW = \sum_{k\in K}\left((Q_k^{DA} + Q_k^{PR})w_k\right) - \sum_{k\in K}\left((D_k^{RU} + Q_k^{EInvRU})w_k\right) - \sum_{m\in M}(D_m^{RC} + Q_m^{EInvRC}) \quad (6.2)$$

The 3rd objective is to minimize the total purchased cost of EOL products from suppliers. Each supplier provides different statuses of EOL products with different sales prices. To avoid extra costs for inventory and disposal, only the required EOL products should be purchased to satisfy the demands of the reused component and recycled materials. Hence, the total purchased cost of EOL products from suppliers can be formulated as

$$TPURC = \sum_{i\in I}\sum_{j\in J} Q_{ij}^{EOL} p_{ij} \quad (6.3)$$

The 4th objective is to minimize the total outside procurement cost. Supply shortage of the demands for reused components and recycled materials is not allowed in this model. However, it is difficult to fulfill the demands of reused components and recycled materials from the purchased EOL product only, because of uncertainties in each component status in the purchased EOL products. Thus, the total outside procurement for additional components is unavoidable to satisfy the demands. The total outside procurement cost can be formulated as

$$TPRC = \sum_{k\in K} Q_k^{PR} prc_k \quad (6.4)$$

Resale revenues of reused components and recycled materials are expressed as the multiplication of demands and corresponding prices, as shown in Eqs. (6.5) and (6.6).

The total disassembly cost, as shown in Eq. (6.7), comprises the sum of destructive and nondestructive disassembly costs. Nondestructive disassembly operations are conducted to remove only good components for reuse without damaging them. Thus, the nondestructive disassembly cost increases over the destructive disassembly cost.

The DTO system has separate inventories for reused components and recycled materials. The holding cost of reused components increases over that of recycled materials to maintain the function of the reused components under a good inventory condition. Hence, the total inventory cost comprises the sum of holding cost of reused components and recycled materials and is formulated as shown in Eq. (6.8). Moreover, the DTO has an in-plant recycling facility with a recycling capacity and an out-plant recycling facility without capacity. The total recycling cost is the sum of the recycling costs at both facilities and is formulated as shown in Eq. (6.9). The total disposal cost is the sum of the disposal cost of reused components, hazardous components, and recycled materials. Then, the total disposal cost is formulated as shown in Eq. (6.10)

$$RUR = \sum_{k\in K} D_k^{RU} sru_k \tag{6.5}$$

$$RCR = \sum_{m\in M} D_m^{RC} src_m \tag{6.6}$$

$$TDAC = \sum_{k\in K} (Q_k^{NDA} ndac_k + Q_k^{DDA} ddac_k) \tag{6.7}$$

$$TINVC = \sum_{k\in K} (Q_k^{EInvRU} ruhc_k) + \sum_{m\in M} (Q_m^{EInvRC} rchc_m) \tag{6.8}$$

$$TRCC = \sum_{m\in M} (Q_m^{IRC} ircc_m + Q_m^{ORC} orcc_m) \tag{6.9}$$

$$TDPC = \sum_{k\in K} (Q_k^{RUDP} dpc_k^{RU} + Q_k^{BDDA} hdpc_k) + \sum_{m\in M} (Q_m^{RCDP} dpc_m^{RC}) \tag{6.10}$$

6.2.2 Constraints of DTO system

Formulation of the constraints for the DTO system is explained. Constraints for the number of purchased EOL products and disassembly components are formulated as shown in Eqs. (6.11) to (6.14). Each supplier *j* provides different statuses of the EOL product *i* with supply capacity (Cap_{ij}^{EOL}). Then, Eq. (6.11) ensures that the number of purchased EOL products *i* from supplier *j* (Q_{ij}^{EOL}) does not exceed the supply capacity (Cap_{ij}^{EOL}).

The total number of disassembled components *k* (Q_k^{DA}) is equal to the multiplication of the purchased EOL product *i* from supplier *j* and the number of components *k* in EOL product *i* from supplier *j*, as shown in Eq. (6.12). The DTO system addresses uncertainties in the EOL products as the stochastic disassembly yields of component *k* in EOL product *i* from supplier *j* (yld_{ijk}), which determine whether the components can be reused. Therefore, the total number of nondestructive disassembly components *k* (Q_k^{NDA}) can be formulated as the multiplication of the number of disassembled components *k* (Q_k^{DA}) and the stochastic disassembly yields (yld_{ijk}), as shown in Eq. (6.13).

Meanwhile, the number of destructive disassembly components *k* (Q_k^{DDA}) is the subtraction of the number of nondestructive disassembly components *k* (Q_k^{NDA}) from the total number of disassembly component *k* (Q_k^{DA}) , as shown in Eq. (6.14).

$$Q_{ij}^{EOL} \leq Cap_{ij}^{EOL} \qquad \forall i \in I, \forall j \in J \tag{6.11}$$

$$Q_k^{DA} = \sum_{i\in} \sum_{j\in J}(Q_{ij}^{EOL} Num_{ijk}) \qquad \forall k \in K \tag{6.12}$$

$$Q_k^{NDA} = \sum_{i\in I} \sum_{j\in J}(Q_{ij}^{EOL} Num_{ijk} yld_{ijk}) \qquad \forall k \in K \tag{6.13}$$

$$Q_k^{DDA} = Q_k^{DA} - Q_k^{NDA} \qquad \forall k \in K \tag{6.14}$$

The numbers of reusable and recyclable components are determined based on the reuse (PCT_k^{RU}) and recycling percentage (PCT_K^{RC}) throughout the inspections, as shown in Eqs. (6.15) to (6.18). The number of reusable component *k* (Q_k^{GNDA}) is expressed as the multiplication of the number of the nondestructive disassembly component *k* (Q_k^{NDA}) and the reusable percentage of component *k* (PCT_k^{RU}), as shown in Eq. (6.15). Equation (6.16) ensures that the number of non-reusable component k (Q_k^{BNDA}) is equal to the subtraction of the number of reusable components k (Q_k^{GNDA}) from that of the non-destructive disassembly components k (Q_k^{NDA}). Then, the non-reusable component k (Q_k^{BNDA}) is sent to inspection for recycling.

Similar to the reusable components, the number of recyclable components k (Q_k^{GDDA}) is determined based on the recycling percentage of component k (PCT_k^{RC}), as shown in Eq. (6.17). Equation (6.18) shows that the non-recyclable component k with hazardous material components (Q_k^{BDDA}) is equal to the subtraction of the number of recyclable components k (Q_k^{GDDA}) from remaining components in recycling inspection ($Q_k^{DDA} + Q_k^{BDDA}$).

$$Q_k^{GNDA} = \sum_{i\in I}\sum_{j\in J}(Q_k^{NDA}PCT_k^{RU}) \qquad \forall k \in K \tag{6.15}$$

$$Q_k^{BNDA} = Q_k^{NDA} - Q_k^{GNDA} \qquad \forall k \in K \tag{6.16}$$

$$Q_k^{GDDA} = (Q_k^{DDA} + Q_k^{BNDA})PCT_k^{RC} \qquad \forall k \in K \tag{6.17}$$

$$Q_k^{BDDA} = Q_k^{DDA} + Q_k^{BNDA} - Q_k^{GDDA} \qquad \forall k \in K \tag{6.18}$$

Constraints regarding the number of reused components is represented as shown in Eqs. (6.19) and (6.20). Equation (19) ensures that the number of reused components k (Q_k^{RU}) meets the sum of quantities of initial inventory of reusable components k (Q_k^{SInvRU}), recyclable components k (Q_k^{GDDA}), and outside procurement for reused components k (Q_k^{RUPR}). Equation (6.20) indicates that the number of reused components k (Q_k^{RU}) is equal to or greater than the demand of reused components k (D_k^{RU}).

Regarding to reuse components, the recyclable weight of material m Q_m^{RCW} is obtained to multiply the sum of components made of material m for recycling ($Q_k^{GDDA} + Q_k^{RCPR}$) by the weight w_k and the rate of the recyclable weight of component r_k as shown in Eq. (6.21). The total weight of recycled material Q_m^{RC} is the sum of the initial inventory of recycled material Q_m^{SInvRC} and the recyclable weight Q_m^{RCW} as shown in Eq. (6.22). Equation (6.23) ensures that total weight of recycled materials Q_m^{RC} is equal to or greater than the demand of recycled materials m (D_m^{RC}).

The total number of the outside procurement components (Q_k^{PR}) is equal to the sum of quantities of outside procurement components for reused components (Q_k^{RUPR}) and recycled materials Q_k^{RCPR} as shown in Eq. (6.24).

$$Q_k^{RU} = Q_k^{SInvRU} + Q_k^{GNDA} + Q_k^{RUPR} \qquad \forall k \in K \tag{6.19}$$

$$Q_k^{RU} \geq D_k^{RU} \qquad \forall k \in K \tag{6.20}$$

$$Q_m^{RCW} = (Q_k^{GDDA} + Q_k^{RCPR})w_k r_k \qquad \forall k \in \{K_m | m \in M\} \tag{6.21}$$

$$Q_m^{RC} = Q_m^{SInvRC} + Q_m^{RCW} \qquad \forall m \in M \tag{6.22}$$

$$Q_m^{RC} \geq D_m^{RC} \qquad \forall m \in M \tag{6.23}$$

$$Q_k^{PR} = Q_k^{RUPR} + Q_k^{RCPR} \qquad \forall k \in K \tag{6.24}$$

The DTO has in-plant and out-plant recycling facilities. The recyclable components are first sent to the in-plant recycling facility with the processing capacity (Cap_k^{IRC}), and then to out-plant recycling facilities if the recycled material *m* at the in-plant facility (Q_m^{IRC}) reaches its processing capacity (Cap_m^{IRC}), as shown in Eqs. (6.25) and (6.26).

$$Q_m^{IRC} = \begin{cases} Q_m^{RCW} & Q_m^{RCW} \leq Cap_m^{IRC} \\ Cap_m^{IRC} & Q_m^{RCW} > Cap_m^{IRC} \end{cases} \qquad \forall m \in M \tag{6.25}$$

$$Q_m^{ORC} = Q_m^{RCW} - Q_m^{IRC} \qquad \forall m \in M \tag{6.26}$$

The terms ($Excess_k^{RU}$) and ($Excess_m^{RC}$) in Eqs. (27) and (28) denote the excess number of reused components *k* and recycled material *m* from their demands. The excesses of reused components *k* and recycled materials *m* are sent to the reused and recycled inventory with inventory capacities of the reused (Cap_k^{InvRU}) and recycled (Cap_m^{InvRC}), respectively, as shown in Eqs. (6.29) and (6.30).

The terms (Q_k^{RUDP}) and (Q_m^{RCDP}) in Eqs. (6.31) and (6.32) denote the number of reused components *k* and recycled materials *m* sent to a disposal facility. Equations (6.31) and

(32) indicate that the excesses of inventory capacities of the reused component k and recycled material k are sent to the disposal facility if the inventories are fulfilled with reused component k and recycled materials. Equation (33) ensures that all variables must be non-negative.

$$Excess_k^{RU} = Q_k^{RU} - D_k^{RU} \qquad \forall k \in K \tag{6.27}$$

$$Excess_m^{RC} = Q_m^{RC} - D_m^{RC} \qquad \forall m \in M \tag{6.28}$$

$$Q_k^{EInvRU} = \begin{cases} Excess_k^{RU} & Excess_k^{RU} \leq Cap_k^{InvRU} \\ Cap_k^{InvRU} & Excess_k^{RU} > Cap_k^{InvRU} \end{cases} \qquad \forall k \in K \tag{6.29}$$

$$Q_m^{EInvRC} = \begin{cases} Excess_m^{RC} & Excess_m^{RC} \leq Cap_m^{InvRC} \\ Cap_m^{InvRC} & Excess_m^{RC} > Cap_m^{InvRC} \end{cases} \qquad \forall m \in M \tag{6.30}$$

$$Q_k^{RUDP} = Excess_k^{RU} - Q_k^{EInvRU} \qquad \forall k \in K \tag{6.31}$$

$$Q_m^{RCDP} = Excess_m^{RC} - Q_m^{EInvRC} \qquad \forall m \in M \tag{6.32}$$

$$Q_{ij}^{EOL}, Q_k^{PR}, Q_k^{RUPR}, Q_k^{RCPR}, Q_k^{DA}, Q_k^{NDA}, Q_k^{DDA}, Q_k^{GNDA}, Q_k^{BNDA}, Q_k^{GDDA}, Q_k^{BDDA},$$

$$Q_k^{RU}, Q_m^{RC}, Q_m^{RCW}, Q_m^{IRC}, Q_m^{ORC}, Excess_k^{RU}, Excess_m^{RC}, Q_k^{EInvRU}, Q_m^{EInvRC}, Q_k^{RUDP},$$

$$Q_m^{RCDP}, d_{ps}^{+}, d_{ps}^{-} \geq 0 \tag{6.33}$$

6.2.3. Adaptation of LPP to solve multi-criteria DTO problem

The proposed DTO system has 4 objectives, i.e., maximizing total profit *TP* while minimizing total disposal weight *TDW*, total purchased EOL product cost *TPURC*, total outside procurement cost *TPRC*. To design a DTO system under multiple objectives, LPP is applied with a desirability range set by a DM based on hard and soft classes.

(1) Total profit *TP* (*p*=1): The *TP* in the DTO system is maximized. Then, it belongs to class 2-S (lager is better). The DM needs to set 6 desirability ranges, namely ideal, desirable, tolerable, undesirable, highly undesirable, and unacceptable, by setting 5 limitations of the total profit. Therefore, the mathematical expression of the total profit *TP* is written as shown in Eqs. (33) and (34). The total profit tries to reach the ideal range by minimizing the negative deviation variables $d_{1,s}^{-}$ (s=2, 3, 4, 5) from the *s*th limit of the total profit.

$$TP + d_{1,s}^{-} \geq t_{1,(s-1)}^{-} s = 2, \ldots, 5 \tag{6.34}$$

$$TP \geq t_{1,5}^{-} \tag{6.35}$$

(2) Total disposal weight *TDW* (*p*=2): *TDW* is minimized to reduce the amount of disposal weight in the DTO system. In contrast to *TP*, *TDW* belongs to class 1-S (smaller is better). Then, 6 desirability ranges are set by the DM to calculate the LPP weight by setting 5 limitations as well as *TP*. Therefore, the mathematical expression of *TDW* is shown in Eqs. (6.36) and (6.37). *TDW* is eager to reach the ideal range by minimizing the positive deviation variables $d_{2,s}^{+}$ (s=2, 3, 4, 5) from the *s*th limit of the outside procurement cost of the additional components.

$$TDW - d_{2,s}^{+} \leq t_{2,(s-1)}^{+} \quad s = 2, \ldots, 5 \tag{6.36}$$

$$TDW \leq t_{2,5}^{+} \tag{6.37}$$

(3) Total purchased cost of EOL products *TPURC* (*p*=3): Similar to *TDW*, *TPURC* is is minimized to purchase only the required EOL products to establish the DTO system economically. Thus, *TPURC* belongs to class 1-S (smaller is better) and is formulated as shown in Eqs. (6.38) and (6.39).

$$TPURC - d_{3,s}^{+} \leq t_{3,(s-1)}^{+} \qquad s = 2, \dots, 4 \tag{6.38}$$

$$TPURC \leq t_{3,5}^{+} \tag{6.39}$$

(4) Total outside procurement cost of additional components *TPRC* (p=4): *TPRC* is also minimized to procure only shortage components for fulfilling the demands of reused components and recycled materials.

$$TPRC - d_{4,s}^{+} \leq t_{4,(s-1)}^{+} \qquad s = 2, \dots, 4 \tag{6.40}$$

$$TPRC \leq t_{4,5}^{+} \tag{6.41}$$

To solve this multi-objective problem using LPP, an aggregate objective function is set to be minimized, as shown in Eq. (6.42). The terms $\widetilde{w}_{ps}^{-}/\widetilde{w}_{ps}^{+}$ and d_{ps}^{+}/d_{ps}^{-} denote the calculated LPPW based on the LPPW algorithm, and the deviation variables from sth desirability ranges of objective p, respectively. The aggregate objective function finds one satisficing solution, which reflects the preferences of the DM.

$$\sum_{p=1}^{4} \sum_{s=2}^{5} (\widetilde{w}_{ps}^{-} d_{ps}^{-} + \widetilde{w}_{ps}^{+} d_{ps}^{+}) \rightarrow Min \tag{6.42}$$

6.3 Numerical example

This section illustrates a design example of the DTO system. Similar to Hasegawa et al (2018, 2019), a desktop computer consisted of 14 parts is used as a product example. The desktop computer has 5 different materials, namely, Circuit board, Polyvinyl chloride (PVC), Iron, Aluminium/Aluminium alloy, and Stainless (SUS). It is assumed that 3 different suppliers provide different statues of computers, respectively. Subsection 6.3.1 displays parameters of the DTO system. Subsection 6.3.2 sets desirability ranges with LPP classes and calculates the mathematical weight. Subsection 6.3.3 discusses the results of the numerical experiment.

6.3.1 Input data of DTO system

This subsection sets parameters of the DTO systems. Table 6.1 shows EOL purchase price and supply capacity from supplier. Table 6.2 shows the stochastic disassembly yields of each component provided from different suppliers. The stochastic disassembly yields depend on each component condition of collected the EOL products, and determine whether the components can be reusable or not. This study assumes that 3 different suppliers provide 3 different conditions of the EOL computers, respectively. Table 6.3 shows component information, demand, and selling price of reused component, and costs. The material type and weight for each component as shown in table 6.3 are introduced from Hasegawa et al. (2018, 2019). The reused components demand for each component in table 6.3 is set based on Hasegawa et al. (2018, 2019). For example, reused demands of switch and inside switch are set 0 (unit) since they are set as non-reusable components in Hasegawa et al. (2018, 2019). Reusable percentage indicates a passing rate of inspection for reused component. Recyclable percentage means a rate of component with hazardous materials. The components with hazardous materials cannot be recycled, and disposed of.

The recycling material demand is set based on Hasegawa et al. (2018, 2019). This study assumes that all components made of circuit board in the desktop computer are difficult for material recycling. Then, the recycled demand of circuit board is set as 0 (g) as shown in table 6.4. Moreover, each purchased desktop has 1 (unit) of each component. Storage capacities of each reuse component and recycled weight are set as 50 (unit) and 100,000 (g), respectively. In addition, the process capacities at the in-plant recycling facility for each material is set as 50,000 (g). The initial inventories for each component and material are set as 0 (unit) and 0(g), respectively.

Table 6.1 EOL purchase price and supply capacity from supplier

Supplier	1	2	3
Purchase price ($)	28	25	25
Capacity (unit)	250	270	260

Table 6.2 Stochastic disassembly yields of each computer component (%)

	Fan controller	Cable	PCI board	HDD	FDD	CDD	Swith	Big fan	Big fan cover	Small fan	Inside switch	Speaker	Memory	Mother board
Supplier 1	0.93	1.00	1.00	0.76	0.75	0.81	0.64	0.93	0.70	0.92	0.99	0.66	0.85	0.50
Supplier 2	0.62	0.62	0.95	0.79	0.93	0.92	0.51	0.56	0.81	0.52	0.82	0.87	0.65	0.64
Supplier 3	0.83	0.98	0.82	0.81	0.73	0.81	0.81	0.83	0.84	0.81	0.84	0.82	0.59	0.95

Table 6.3 Component information, demand, selling price of reused component, and cost

Component	Material type	Weight (g)	Reused component demand (unit)	Selling price of reused component ($)	Reussable percentage (%)	Recyclable percentage (%)	Rate of recyclable weight (%)	Disassembly cost ($)		Outside procurement cost ($)	Inventory cost of reused component ($)	Disposal cost ($)	
								Non-destructive	Destructive			Reused component	Hazardous component
Fan controller	Circuit board	50	290	15	82	0	0	1.4	0.9	14.0	3.7	2.5	4.0
Cable	PVC	220	0	0	0	95	100	1.5	0.8	12.0	3.5	2.0	4.0
PCI board	Fe	300	280	13	93	0	0	1.2	0.9	15.0	3.4	1.9	4.0
HDD	Al/Al alloy	1,500	300	15	85	99	100	1.3	0.7	12.0	3.9	2.2	4.0
FDD	Al/Al alloy	500	0	0	0	99	100	1.5	0.8	12.0	3.3	1.7	4.0
CDD	Al/Al alloy	1,000	290	17	80	97	100	1.3	0.9	12.0	3.6	2.1	4.0
Switch	Circuit board	50	0	0	0	0	0	1.3	0.9	15.0	3.6	2.5	4.0
Big fan	Al/Al alloy	1,000	270	15	93	98	100	1.6	1.1	12.0	3.8	2.2	4.0
Big fan cover	Fe	100	320	18	73	96	100	1.4	0.7	11.0	3.7	1.7	4.0
Small fan	Al/Al alloy	500	330	15	70	97	100	1.3	1.1	12.0	3.9	1.7	4.0
Inside switch	Fe	50	0	0	0	95	100	1.4	1.1	15.0	3.8	2.2	4.0
Speaker	SUS	300	310	17	92	99	100	1.5	1.1	14.0	3.8	2.3	4.0
Memory	Circuit board	100	290	16	82	0	0	1.5	1.1	13.0	3.7	2.1	4.0
Mother board	Circuit board	500	310	14	89	0	0	1.2	1.0	13.0	3.7	1.7	4.0

Table 6.4 Demand, selling price and recovery process cost for each material type

	Recycled material demand (g)	Selling price of recycled material ($)	Inventory cost of recycled material ($)	Recycling cost ($)		Disposal cost of recycled material ($)
				In-plant	Out-plant	
Circuit board	0	0	0.37	1.0	2.1	2.3
PVC	4,000	4.5	0.38	1.0	2.1	2.5
Iron	18,000	3.4	0.37	1.0	2.1	2.2
Al /Al alloy	72,000	4.9	0.39	1.0	2.1	2.1
SUS	20,000	5.5	0.35	1.0	2.1	2.9

6.3.2 Desirability ranges and LPP weight

There are 4 objective functions in the DTO system as presented. The total profit is maximized, while the total disposal weight, total purchased EOL product cost, and total procured cost of additional component are minimized. With respect to LPP classes of each objective function, total profit belongs to Class-2S "Larger-is-better", and other 3 objective functions belong to Class-2S "Larger-is-better". To set reasonable desirability ranges for each criterion, the disassembly production planning in the DTO system was solved as single models for each criterion. Table 6.5 shows results of single models for each criterion. Based on the results of the single models as shown in table 6.5, table 6.6 sets the desirability ranges of objective functions. The LPP weight can be calculated using the desirability ranges as shown in table 6.6. Table 6.7 shows the calculated LPP weight given in this study.

Table 6.5 Results of single models for each criterion

Objective function	Criteria			
	TP ($)	*TDW* (g)	*TPURC* ($)	*TPRC* ($)
Max *TP*	409,715.95	5,993.00	478.47	39,503.04
Min *TDW**	303,709.00	0.00	0.00	45,327.50
Min *TPURC**	303,709.00	0.00	0.00	45,327.50
Min *TPRC*	-3,946,676.21	1,387,029.56	15,277.53	3,234.59

Note: Results with * was obtained by solving as linear programming relaxation problem

Table 6.6 Desirability ranges of objective functions

	Profit ($)	Disposal weight (g)	Purchase cost for EOL product ($)	Procurement cost for component ($)
Ideal	>=420,000	5,000<=	700<=	3,000<=
Desirable	[400,000, 420,000)	(5,000, 10,000]	(700, 1,500]	(3,000, 5,000]
Tolerable	[380,000, 400,000)	(10,000, 20,000]	(1,500, 2,500]	(5,000, 15,000]
Undesirable	[350,000, 380,000)	(20,000, 27,000]	(2,500, 5,000]	(15,000, 30,000]
Highly undesirable	[300,000, 350,000)	(27,000, 30,000]	(5,000, 6,500]	(30,000, 36,000]
Unacceptable	<300,000	30,000>	6,500>	36,000>

Table 6.7 Calculated LPP weight

Objectives	$\tilde{w}_{i,2}^{+}$	$\tilde{w}_{i,3}^{+}$	$\tilde{w}_{i,4}^{+}$	$\tilde{w}_{i,5}^{+}$
Profit ($)	0.2500	1.0100	2.9736	8.5688
Disposal weight (g)	1.0000	1.5200	15.6240	195.2294
Purchase cost for EOL product ($)	6.2500	18.9500	25.6032	375.9437
Procurement cost for component ($)	2.5000	0.0200	5.9472	98.2195

6.3.3 Results of disassembly production planning in DTO system

Results of the numerical experiment is discussed in the subsection. The numerical experiment was conducted on the same desktop PC (Windows 8.1 with Intel(R) Core(TM) i5-4460 CPU@3.20GHz) by using an optimization solver named glpk (GLPK - GNU Project).

Table 6.8 shows value and aspiration level of each objective function. The aspiration level indicates which desirability ranges in table 6.7 correspond to the obtained value of the objective function. The aspiration levels of the profit, disposal weight and procuremtn cost for components became undesirable, undesirable, and highly undesirable, respectively. On the other hand, the aspiration levels of the purchases cost for EOL products weight became desirable. The procurement cost for component 27 times higher than the purchase cost of EOL product, even though procurement cost was minimized. That would lead to different aspiration levels between purchased cost of EOL products and procurement cost of outsourcing component. Moreover, it seems that most of reused and recycled components was provided from outsourcing component supplier.

The total recycling rate of the whole DTO system can be defined as the weight ratio of reused components and recycled materials against the total input weight of the EOL products and outsourcing components. In the numerical experiments, the total recycling rate of the whole DTO system became 99%.

Table 6.8 Value and aspiration level of each objective function

Objectives	Value	Aspiration level
Profit ($)	373,983.90	Undesirable
Disposal weight (g)	20,810.00	Undesirable
Purchase cost for EOL product ($)	1,355.00	Desirable
Procurement cost for component ($)	35,987.00	Highly undesirable

Table 6.9 Supply, inventory, and disposal quantities of each reuse component

Component name	Supply of reuse component (unit)			Inventory of reused component (unit)	Disposal Quantity (unit)	
	Reused components recovered from purchased EOL product (RU^{rec})	Reused components procured from outside component supplier (RU^{pro})	Total supply of reuse component (=RU^{rec} + RU^{pro})		Reused component	Hazardous waste
Fan controller	37	253	290	0	0	13
Cable	0	0	0	0	0	3
PCI board	44	236	280	0	0	6
HDD	33	267	300	0	0	0
FDD	0	0	0	0	0	0
CDD	32	258	290	0	0	2
Switch	0	0	0	0	0	50
Big fan	42	228	270	0	0	0
Big fan cover	27	293	320	0	0	1
Small fan	31	299	330	0	0	1
Inside switch	0	0	0	0	0	2
Speaker	33	277	310	0	0	0
Memory	32	258	290	0	0	18
Mother board	28	282	310	0	0	22
Total	339	2651	2990	0	0	118
Average	24.21	189.36	213.57	0.00	0.00	8.43
Standard deviation	16.55	125.77	141.02	0.00	0.00	13.97

Table 6.10 Supply, inventory, and disposal quantities of each recycled material

Material type	Supply of recyclable material (g)			Inventory of recycled material (g)	Disposal weight of recycled material (g)
	Recycled material recovered from purchased EOL product (RC^{rec})	Recylcled material procured from outside component supplier (RU^{pro})	Total supply of recycled material (=RC^{rec} + RC^{pro})		
Circuit board	0	0	0	0	0
PVC	10,340	0	4,180	6,340	0
Iron	4,600	13,400	18,050	0	0
Al /Al alloy	83,500	0	75,000	11,500	0
SUS	5,400	14,700	20,100	100	0
Total	103,840.00	28,100.00	117,330.00	17,940.00	0
Average	20,768.00	5,620.00	23,466.00	3,588.00	0.00
Standard deviation	35,259.53	7,709.22	30,079.14	5,198.24	0.00

Tables 6.9 and 6.10 show supply, inventory, and disposal quantities of each reused component and recycled material, respectively. Although the aspiration level of disposal weight became undesirable, the disposal reusable components and recyclable materials became 0 (unit) and 0 (g), respectively. This situation could be caused by components with 0% recyclable percentage. These parts such as fan controller, PCI board, switch, memory, and mother board as shown in table 6.3 were not recycled, even though they did not contain hazardous materials. Then, all those components sent to the recycling facilities were disposed of. Therefore, the aspiration level of disposal weight became undesirable.

6.4 Summary of disassembly to order system

This study proposed a DTO system with recycling rate under stochastic disassembly yields based on Kinoshita, Yamada and Gupta (2019b). The DTO system could be designed by using LPP. The desktop computer was used to demonstrate a design example. There were 3 main findings from the numerical experiments as follows:

- The total recycling rate of the whole DTO system became 99%. The total recycling rate of the whole DTO system, which could be defined the weight ratio of reused components and recycled materials against the total input weight of the EOL products and outsourcing components.
- The number of storage for all reused components were 0 (unit). On the other hand, the volume of the recycled Al/Al alloy in the storage became 11,500 (g).
- The total procurement cost of components became 27 times higher than the total purchased cost of EOL products. Therefore, most of the reused components and recycled materials procured from outside supplier.

Future studies should consider disassembly precedence relationships of EOL products, multiple types of EOL products and other environmental loads such as CO_2 emissions (Kinoshita et al, 2018a; Igarashi et al, 2016; Hasegawa et al, 2019).

7. Conclusions and future studies

This study proposed 3 design methods for material and component sustainability with reuse and recycling, and evaluated materials and components within the EOL products in terms of environmental and economic aspects for component reuse and material recycling. The proposed methods are expected to be used to manage materials and components in the product life cycle.

7.1 Decision support model for material selection

Chapter 3 proposed a decision support model of environmentally friendly and economical materials selection for costs, recycling rate and CO_2 emissions With regards to main contributions, there are 2 main contributions. One contribution is to enhance usage possibility of alternative materials with lower cost, disposal weight and CO_2 emissions than materials in the past design. The other contribution is to promote environmentally conscious manufacturing. Environmentally conscious manufacturing is defined as green principles that are concerned with developing methods for whole product life cycle from conceptual design to the EOL disposal to meet satisfy environmental standards and requirements (Ilgin and Gupta, 2010).

The practical implications are also listed as follows:

- The proposed model can be effective and useful in the concept design phase to propose candidate materials for the assembly products. By using this model, the materials, which have not been examined even though they are recyclable with lower cost, could be suggested for the product designers.
- The proposed model could be adopted to any types of assembly products in the concept design phase. This is because the decision support model can evaluate the costs, disposal weight and CO_2 emissions using weight and material type for each part only.
- It would increase or make a chance of material innovation. When the decision support model might select unfeasible materials in the current technology by evaluating only cost and recyclable weight, the suggestion would generate positive motivation and avoid combinational explosion for creating the new material innovation. Thus, the

decision support model would be also used to identify potential materials and to give directions for the material innovation by research and development.

However, limitations of this study still remain as follows:

- Each part is assumed to consist of only one representative material to evaluate the costs, disposal weight and CO_2 emissions in the decision support model. Actually, a part of assembly products is often consisted of several types of materials. In those cases, the decision support model can grasp the recyclable weight, CO_2 emissions and costs in spite of calculating them exactly.
- It is assumed that the suggested material can have the same function and performance as ones at the default design. By switching alternative materials with ones of default design, the functions and performances would not be sometimes satisfied.
- The disassembly precedence relationships among the disassembly tasks are not treated. Then, the recycling cost for a certain part in the decision support model would become higher than the expected recycling cost due to its disassembly precedence relationships among the disassembly takas.

Future studies should consider the change of selling price of recycled materials for alternative material selection, disassembly precedence relationships, and validate the selected materials in terms of product design.

7.2 2 types of bi-objective disassembly parts selection

Chapters 4 and 5 focused on materials removed from the end-of-life (EOL) assembly products, conducted the environmentally friendly and economical disassembly parts selection by using goal vector method by goal programming (GP). Next, the recycled material types, weights and recycling cost were analyzed in order to identify the bottlenecks for enhancing the cost effectiveness by comparing the bi-objectives for recycling rate and cost and for CO_2 saving rate and recycling cost. The main findings of this study were as follows:

- Pattern 1) all ranges is the best method for finding solutions, and harmonizes the recycling/CO_2 saving rate and cost.
- Pattern 2) division into 3 areas suggests multiple alternative solutions for the decision-makers to show the Pareto optimal ones.
- The desirable number of divisions would be 3 or 4 in the experiments.
- Different targets ranges of CO_2 saving or recycling rate by GP obtained different types of materials, recycled weights for each material and cost in spite of setting the same objective functions for recycling rate and cost and for the CO_2 saving rate and recycling cost.
- There were different recycled weights and cost obtained from the disassembly parts selection between bi-objectives for recycling rate and cost and for CO_2 saving rate and recycling cost. The bi-objective for recycling rate and cost obtained the heaviest materials contained of the EOL assembly products, while the bi-objective for CO_2 saving rate and recycling cost obtained PMMA, which emits more GHGs emissions at material production phase.
- It found out that it was not found the obvious differences between the total CO_2 saving E and recycling rates R in terms of the total recycling cost in environmentally friendly and economical disassembly parts selection.
- The same trends were observed that the total recycling cost C increased as the total CO_2 saving E or recycling rates R increased. However, there were not the same combinations of the selected parts in bi-objectives for recycling rate and cost and for CO_2 saving rate and cost.

Future studies should adopt the method to other assembly products and consider not only the material recycling but also other life cycle options such as remanufacturing and reuse, and use real data such as the disassembly time and cost.

7.3 Disassembly production planning in DTO system

Chapter 6 proposed a disassembly-to-order (DTO) system under stochastic disassembly yields computed using linear physical programming (LPP), demonstrating a design example and discussing the results. The DTO system, which had over 200 variables and 4 criteria, could be solved with linear mixed-integer programming. All quantities for each process in the DTO system were rounded to become integer based on the results.

The proposed disassembly production planning in the DTO can determine the number of components and the volumes of the material for each recovery process by inputting desirability ranges for each criterion. With respect to LPP challenges, the LPP method did not seek and compare all feasible solutions in the experiments. Therefore, there may be better solutions to satisfy the decision maker preferences.

Future studies should consider disassembly precedence relationships of end-of-life (EOL) products and lot sizes for the number of purchased EOL products from suppliers. Moreover, remanufacturing and reaming lifetime of removed components from the EOL products should be taken account of recycling processes.

7.4 Implications and potential impacts by using proposed 3 decision making models

7.4.1 Implications

The proposed models are effective for assembly products with 3 features. One feature is that the assembly products have multiple key parts. The key parts can be defined as much higher costs and environmental loads than other parts. The second feature is that assembly products have complex disassembly precedence relationships among tasks. The last feature is that assembly products are consisted of multiple types of materials. The detailed explanations for each feature as follows:

- Assembly products with multiple bottleneck parts

The proposed models can be effective since the assembly products with multiple bottleneck parts will be required to determine which materials should be selected for each bottleneck part, and which bottleneck parts should be disassembled. In contrast, if the assembly product has only one key part, the decision maker (DM) should pay attention only the key parts since the impacts of whether the key part can be adopted to the material or disassembled on the total costs and environmental loads largely. Thus, the DM does not need the decision support models.

- Assembly products with complex disassembly precedence relationships among disassembly tasks

The disassembly parts selection is effective to determine which parts should be disassembled since the complex disassembly precedence relationships make the determination of the disassembly parts selection more difficult manually. The proposed disassembly parts selection can determine the combination of disassembly parts automatically to satisfy the desirability of the DM by inputting the recycling rate, CO_2 saving rate and cost for each part, and disassembly precedence relationships.

In contrast, if the assembly products have simple disassembly precedence relationships among disassembly tasks, the DM can prioritize the disassembly pars based on only bill-of-materials (BOM). This is because the DM should be select the parts with higher recycling rate or CO_2 saving rate and lower recycling costs listed in a BOM.

- Assembly products consisted of multiple types of materials.

The proposed material selection method is effective for the assembly products consisted of multiple types of materials. Since most of assembly products is consisted of a variety type of materials, the environmental loads for each part are different. Even though the parts have the same weight, the CO_2 emissions and recycling rate become different because of different material production and recycling processes. Thus, the DM is required to evaluate the recycling rate, CO_2 emissions, and cost for each part simultaneously for material selection. The proposed material selection can be effective for most of the assembly products.

In a case of the assembly product consisted of single material, disassembly to separate for each part is not required. Then, the decision support of disassembly parts selection is not required. However, the types of products consisted of single material are very limited.

By summarizing discussions, the assembly products with these features are effective for the decision support models.

Parts: There are multiple bottleneck parts

Product structure: Simple disassembly precedence relationships

Material type: There are multiple types of materials

By adopting the proposed decision making methods to basic home electric appliance such as televisions, air conditioners, washing machines and refrigerators, the methods would contribute to reduction of the recycling fee for these basic home electric appliance. For example, the recycling fee of the televisions and air conditioners are 2,916 yen and 972 yen at least (Ministry of Economy, Trade and Industry, Quick Understanding Proper Recycling for Basic Home Electric Appliances). These higher recycling fees would leads the collected rate, which was defined as a rate of the number of collected volume against the production volume, was only 50.7%, according to the Recycling data book 2018 (Japan Environment Management Associate for Industry). It was noted there was time gap between the moment of collection and production of the assembly products.

The proposed models can support to select the recyclable materials at the product design phase and to determine which and how many parts should be disassembled at the disassembly production phase economically. Therefore, the proposed decision support models will be expected to promote recycling the basic home electronic appliances with the EOL status stored in houses.

7.4.2 Potential impacts

The proposed 3 types of decision makings focus on the material type of assembly products and have the same environmental and economic objective functions, namely maximizing recycling rate, minimizing CO_2 emissions, and minimizing costs. By adopting the proposed methods to the assembly products, 3 potential effects on product and production designs can be expected.

One impact is help the DM support of improvement plans such as changing not only materials but also product structure and disassembly tasks in advance in product and disassembly production designs for increasing recycling rate. In planning material improvements, the selected materials in the decision support model for material selection is used as input data for disassembly parts selection and disassembly-to-order (DTO) to examine whether the recycling rate can be increased economically or not by selecting the recommended materials.

Similar to the material improvement plan, the improvement plans for design structure and disassembly tasks can be examined by using the proposed 3 methods. There will be a case that changing materials are not effective to increase recycling rate due to disassembly precedence relationships or disassembly tasks. In this case, reducing fastener in product design and changing disassembly tasks in disassembly production design can be brought as improvement plans by using the proposed methods. Therefore, by using the proposed models, it can narrow down the candidate improvement plans from a variety type of candidates such as changing materials, product structures, tasks, etc. in product and production designs.

The second impact is application to demand-to-supply management with reused components and recycled materials. This application can be expected to bring not only promotion of material circulation but also reduction of procurement costs. The 3 decision makings involve determination of required volumes for each material type in product design and determination of supplied volumes of reused components and recycled materials in disassembly production design. Thus, these 3 models can be expected to manage demanded and supplied materials by reuse and recycling. This management will lead to promotion of material circulation and procurement costs at virgin material production.

The last impact is to support research directions for new material development. The material selection in this study does not treat material features such as Young's modulus and stiffness property. Then, the infeasible materials may be recommended for a certain part from existence materials. On the other hand, by inputting the recommended materials into disassembly parts selection and DTO in this study, these models can be estimate recycling rate and costs in adopting the recommended materials.

These findings of recycling rate and costs will give motivation for developing new material based on the selected material in the material selection so as to satisfy the required material properties.

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関連論文

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2) Yuki Kinoshita, Tetsuo Yamada, Surendra M. Gupta, Aya Ishigaki, Masato Inoue, Disassembly Parts Selection and Analysis for Recycling Rate and Cost by Goal Programming, Journals of Advanced Mechanical Design Systems and Manufacturing, Vol.10, No.3, pp.1-15 (2016), DOI: 10.1299/jamdsm.2016jamdsm0052，査読有，4 章に関連

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